Northwest Climate Science Center Final Report

Administrative

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Project Title: Extended Monitoring and Modeling of Climate Change Effects on Pacific Northwest Wetlands
Agreement Number: GS276A-A
Date of Report: 12/20/2014
Period of Time Covered by Report: 9/21/2012 – 12/20/2014
Total Cost: $267,046

Public Summary

Wetlands are widely recognized as important ecosystems that provide critical services for natural communities and human society, including nutrient cycling, wildlife habitat and provisioning, water storage & filtration, carbon sequestration, and agriculture & recreation. Wetlands challenge our current scientific capacity because of their sheer number, their wide range of sizes, and their dynamic nature. As a result, wetlands are understudied compared to other ecosystem types. However, wetlands are thought to be among the most sensitive ecosystems to climate change, so the dearth of scientific resources has accelerating consequences going forward. Our goal in this project was to address the deficiency in wetland resources by developing new approaches and technical tools to better understand wetlands in general and to more effectively manage and conserve wetlands under a changing climate. By focusing our efforts on a range of wetland types, our goal was to better characterize landscape-scale climate change impacts to wetlands across the Pacific Northwest region in support of ongoing assessment and adaptation efforts. Our approach was designed in collaboration with natural resource managers, and involved three methodological advances. First, using remote sensing approaches, we developed new methods for mapping wetlands and reconstructing historical wetland hydrologic dynamics. Second, we used the Variable Infiltration Capacity model, a regional-scale hydrologic model, to hindcast historical wetland dynamics and project the future impacts of climate change on wetlands. Third, we linked these approaches with ecological data to evaluate the impacts and risk of climate change to several classes of wetlands across three ecoregions of Washington state. In the process we developed or collected multiple new datasets on wetland distributions, dynamics, and species occupancy. This work has broad societal value in deepening our understanding of wetland dynamics over time; creating new tools that enable better management and conservation of wetlands and the ecological services that they provide; and enriching conservation and climate adaptation planning efforts with resource and evidence-based decision power.

Technical Summary

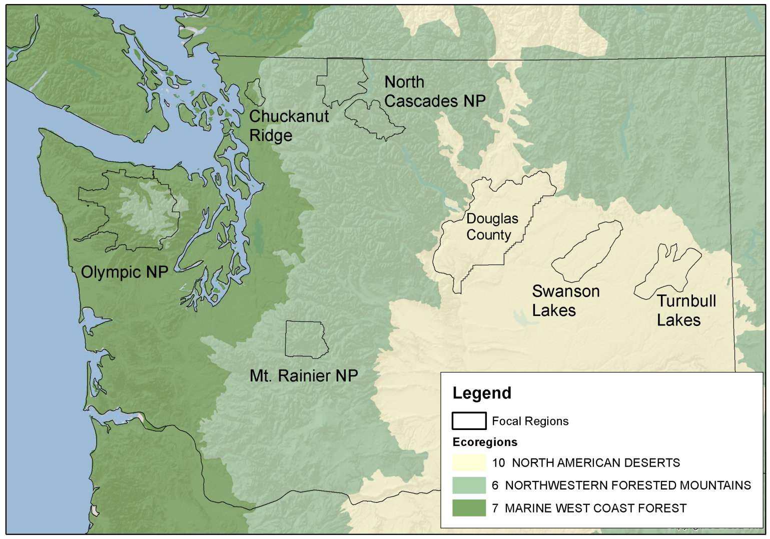
The goals of our project were to 1) develop remote-sensing methods to monitor wetland dynamics and build historical datasets of wetland hydroperiod and areal extent, 2) establish focal field sites over diverse ecoregions and collect key hydrologic data to support the validation of hydrologic models and remote sensing applications, 3) advance hydrologic modeling of climate impacts on wetlands by extending existing work to provide more detailed modeling of hydroperiod for focal sites, and incorporate water temperature dynamics, 4) develop ecological models to relate hydrologic changes to impacts on wetland communities, and 5) synthesize these approaches to connect downscaled climate model projections to wetland impacts at the landscape scale. Funding from the Northwest Climate Science Center made it possible to meet each of the goals of the project and develop a new and well-integrated suite of hydrologic methods and data resources to advance the field. In addition to tangible products, the research process and outcomes have given us a much clearer sense of the constraints and opportunities for further research development by highlighting, for example, where macroscale hydrologic models do and do not work in reconstructing historical wetland dynamics and thus projecting future climate impacts; the spectrum of remote-sensing resources needed for different levels of accuracy in wetland mapping and remote classification; and key questions to further explore regarding patterns and drivers of hydrologic change and their ecological implications. Major research accomplishments include the successful testing of the first suite of macroscale projections of climate impacts to wetlands; novel approaches for reconstructing hydrologic data for 1000's of ponds that would otherwise be lost in time; and synthesis of these approaches for application to wetland adaptation planning in our study regions. These advances are unique in wetlands science and help point towards ways forward in research, conservation, and management.

Note: Portions of Sections 2, 3, and 4 under the headings "Remote-Sensing of Wetlands" and "Climate-Hydrologic Modeling" are excerpted and condensed from Halabisky et al. in review and Lee et al. in review respectively.

EXECUTIVE SUMMARY

Purpose & Objectives

Objective 1: Develop **remote-sensing methods** to monitor wetland dynamics, past and present.
Objective 2: Establish **focal field sites over diverse ecoregions**.
Objective 3: Advance **hydrologic modeling** of climate impacts on wetlands.
Objective 4: Develop **ecological models** to relate hydrologic patterns with species occupancy.
Objective 5: Synthesize these approaches to connect climate projections to wetland impacts at the landscape scale.



Geographic Scope

We focused on seven focal areas of Washington State, spanning montane and alpine regions of the Cascade and Olympic mountains, arid lands of the Columbia Plateau, and Puget Sound lowlands forest.

Advances & Key Findings

Remote Sensing: We developed new methods for mapping and classifying wetlands using remotely sensed data, which significantly improve upon existing wetland inventories. We also developed new methods for reconstructing historical hydroperiods that generated detailed and unique datasets on wetland hydrologic dynamics (e.g. 25 years of reconstructed hydroperiod data for 2,475 ponds). These data begin to address the severe dearth of historical data on wetland dynamics, making it possible to assess baselines and develop physically-based models needed to project climate impacts.
Field Monitoring: We collected three years of field data on wetland hydrology and amphibian habitat use, and developed a new method of water depth monitoring using iButton dataloggers.
Climate-Hydrologic Modeling: We developed the first macroscale models of wetland dynamics, using the Variable Infiltration Capacity (VIC) hydrologic model. We used the VIC model linked to downscaled climate projections to develop the first projections of climate impacts to wetlands at regional scales. We applied this approach to wetlands in three ecoregions.
Ecological Modeling: We found species-specific variation in habitat use, with all species at risk of some habitat loss due to climate change, most notably the Cascades frog.
Synthesis: Wetland habitats used by amphibians are both the most poorly mapped and the most vulnerable to climate change. The distribution of hydrologic risk varies with geography.

Management Products

Remote-sensing: New wetland inventories, reconstructed hydroperiod datasets, and new remote-sensing approaches that can be applied in other regions and to additional wetland types.
Field Monitoring: Datasets can support additional wetland species and hydrologic assessments.
Climate-Hydrologic Modeling: Climate projections specific to wetland change.
Ecological Modeling & Synthesis: Maps of high-risk areas of amphibian habitat loss.

1. Purpose and Objectives

Our project addressed central questions of wetland hydrology, ecology, conservation, and management. We focus on lentic habitats, i.e. ponds, lakes, and shallow wetlands. We serve multiple communities: 1) basic researchers in need of more robust scientific approaches for studying wetlands and generating and testing hypotheses about wetland hydrology, historical dynamics, and future climate impacts, 2) managers seeking to develop conservation, management, and climate adaptation plans for wetlands, 3) policymakers seeking scientific evidence on which to base decisions regarding wetland regulations and protection, and 4) the general public whose day to day life is influenced in direct and indirect ways by wetlands and the ecosystem services that they provide.

Original Objectives

By focusing our collective efforts on a range of wetland types throughout the region, our ultimate goal was to **explicitly characterize landscape-scale climate change impacts to wetland habitats** in three diverse ecoregions of the Pacific Northwest (PNW) that span representative ecoregions in the NPLCC and GNLCC domains and the PNW as a whole. Specific research objectives and their status are described below.

Objective 1: Develop **remote-sensing methods** to monitor wetland dynamics and build historical datasets of wetland hydroperiod and areal extent.
Status & Changes: Objective met. There were no substantial changes to our research plan from the original.

Objective 2: Establish **focal field sites over diverse ecoregions**, collecting key hydrologic & empirical data to support the validation of models and remote sensing applications.
Status & Changes: Objective met. One minor change to our research plan included the use of data collected by collaborators to calibrate the VIC model for these sites after our water depth dataloggers in Puget Sound lowland field sites were disturbed by animals (including humans). The replacement sites were in nearby wetlands and provide empirical data of comparable or higher data resolution to what we had proposed to collect.

Objective 3: Advance **hydrologic modeling** of climate impacts on wetlands by extending existing work to provide detailed modeling of hydroperiod for focal field sites, and incorporating water temperature dynamics to support ecological modeling.
Status & Changes: Objective met. There were no substantial changes to our research plan from the original. Detailed results and the implications of these results are described below.

Objective 4: Develop **ecological models** to relate hydrologic changes to impacts on wetland communities.
Status & Changes: Our preliminary analyses meet our objectives for identifying amphibian-habitat associations in montane sites. Over the next few months we will be refining our analyses using more sophisticated modeling approaches than those presented here, hence models published in peer-reviewed journals will be extensions of this work. There were no substantial changes to our research plan from the original.

Objective 5: **Synthesize** these approaches to connect downscaled climate model projections to wetland impacts at the landscape scale.
Status & Changes: Objective met for montane sites. The equivocal results from our climate-hydrologic modeling exercise for the Columbia Plateau means that we cannot make a high-confidence assessment of future impacts for amphibians, thus have instead presented key questions stemming from what we do know to consider as this research moves forward.

2. Organization and Approach

Our approach integrates research methods and products developed at multiple spatial scales. We focus on three ecoregions of the Pacific Northwest (Figure 2.1): montane ponds and lakes in the Cascade and Olympic mountains, a wide range of wetlands in the Columbia Plateau, and a selection of forested wetlands in Puget Sound lowlands along Chuckanut Ridge near Bellingham. Focal regions in the mountains include Upper Lena Lake region and Seven Lakes Basin and adjacent regions (Deer Lake, Potholes, Wye Lakes) of Olympic National Park; Palisade Lakes, Spray Park, and Mazama Ridge within Mount Rainier National Park; and Dagger Lake region and select individual ponds adjacent to Highway 20 in North Cascades National Park. In the Columbia Plateau, focal regions include Douglas County, Swanson Lakes Wildlife Area, and Turnbull Lakes National Wildlife Reserve. Puget lowlands sites are found on Chuckanut Ridge south of Bellingham. In montane and Columbia Plateau regions, we modeled and classified wetlands using remote sensing methods, with advanced analyses in the Columbia Plateau. We modeled the historical hydrologic dynamics and projected future dynamics under climate change for a suite of wetlands across all three regions. We collected on-the-ground hydrologic and ecological data in focal montane sites. Products developed from each part of the project can be used independently, and have been synthesized to assess the vulnerability of montane amphibians to climate change as a case study. Our approach did not change substantially from the original approach outlined in our research proposal. However, as the research progressed we developed a more detailed approach and responded to our findings in an iterative way, as described below.

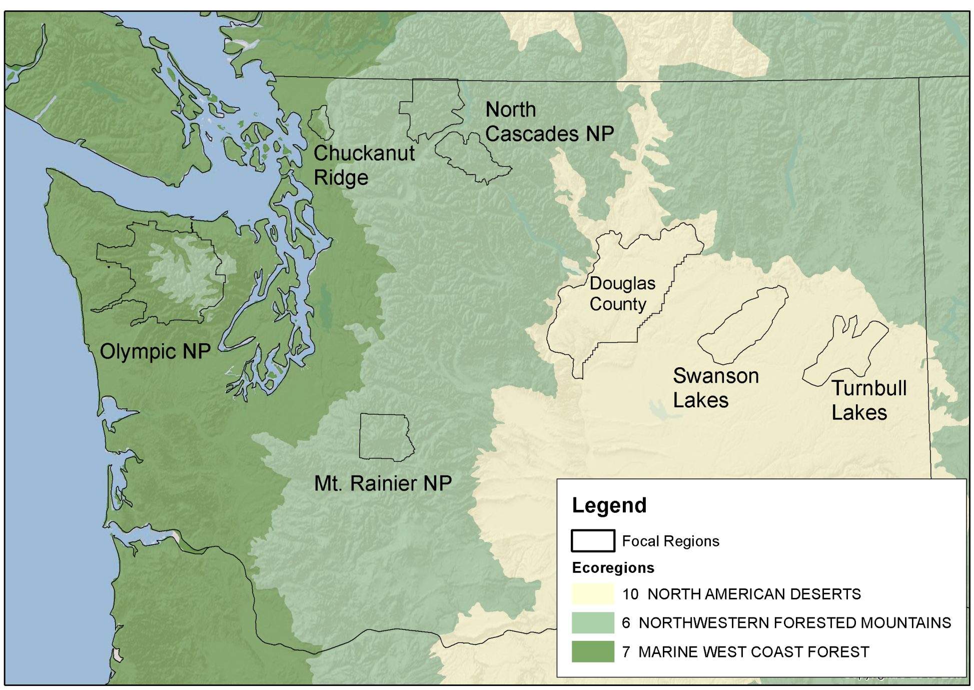


Figure 2.1
Focal field regions for the Northwest Climate Science Center project.

2.1 Remote-Sensing of Wetlands

For this project we developed two new remote sensing methods to map and characterize wetlands. The first technique uses high resolution datasets (multiple years of aerial imagery, LiDAR, and thematic layers) to automate the delineation and classification of wetlands in montane sites. This method relies on object based image analysis (OBIA), a technique that simulates human pattern recognition (Blaschke 2010). The second remote sensing method combines high resolution imagery with a time series of Landsat satellite imagery to reconstruct surface water hydrographs for individual wetlands in the focal regions of the Columbia Plateau over the past thirty years.

Montane Wetlands

Mountainous landscapes represent particular challenges for remote sensing analysts due to the effect of shadows caused by steep topography and tree canopy, which are present in any given date of aerial imagery. Shadows obscure wetlands while the tree canopy itself can directly block the visibility of wetlands underneath. This creates confusion in images because the pixels for the cast shadow may have the same spectral signature as that of the wetlands containing water. In addition, mountains are covered in snowfields, which have different spatial extents at different times of the year. In years with heavy or late season snowfall some wetlands may never be exposed or completely snow-free. Mapping wetlands in these landscapes is challenging as one needs to acquire imagery that not only takes into account the timing of wetlands drying, which begins early in the season, but also the presence of snowfields, which can persist late into the season. Because montane wetlands fall on an elevational gradient some wetlands may be under snow in high elevations, while others may be completely dried out. As a result of these inherent complexities, wetland inventories in these landscapes often omit large numbers of wetlands or have substantial classification errors. Looking forward, current mapping techniques do not provide detailed wetland hydrologic information necessary for making climate change projections and landscape level assessments.

We had two objectives in developing methods for mapping wetlands in montane landscapes. The first was to assess the accuracy of using object based image analysis to delineate wetland ponds with the addition of LiDAR derived data products. Secondly, we wanted to identify remote sensing variables that could be used to identify the rate of wetland drying specific to each wetland.

Object based image analysis

Object based image analysis is a remote sensing technique that mimics the way that humans identify objects through pattern recognition. OBIA differs from other remote sensing techniques by aggregating pixels with similar characteristics into objects through a process called segmentation (Blaschke 2010). Because landscape features are analyzed as objects and not just pixels, OBIA allows for the use of additional factors such as shape, texture, and context. The analyst then builds a ruleset using these factors to classify objects into the classes of interest (Figure 2.1.1). The ruleset can then be run on the entire landscape through batch processing. We used Trimble’s eCognition software to develop our OBIA algorithm ruleset. Because our two rulesets includes over 100 rules it cannot be explained in detail here. The entire ruleset is included in Appendix A and is available upon request.

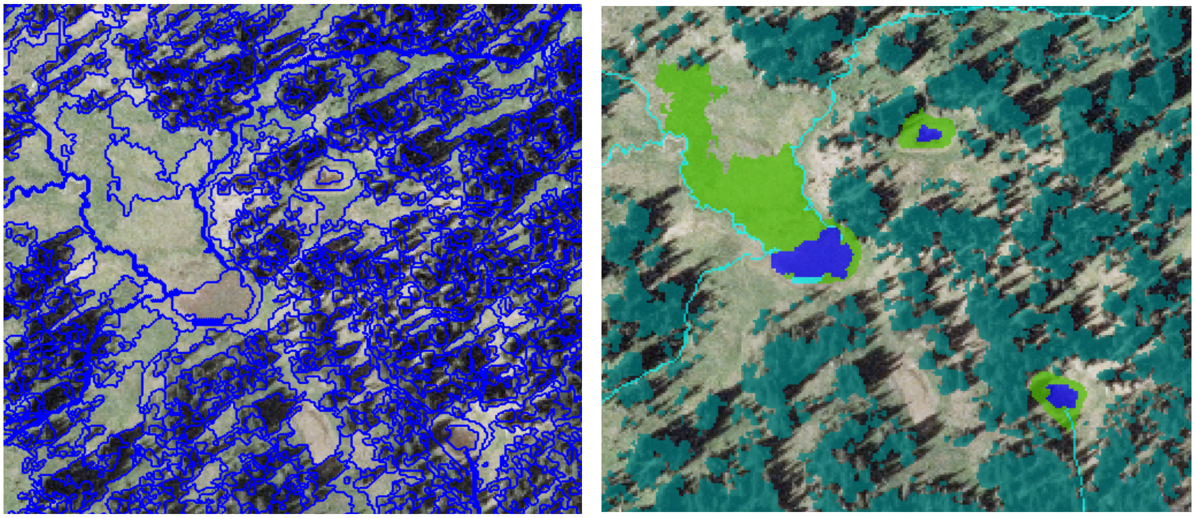


Figure 2.1.1: Example of OBIA classification process. The left hand image demonstrates the segmentation process. Objects are delineated in blue. The right hand image shows the classification output. Blue polygons represent ponds, green polygons represent wetland vegetation, light blue lines represent streams, and dark green polygons represent tree canopy.

Wetland Algorithm

We developed our algorithm using several LiDAR-derived data products, two dates of high resolution aerial imagery (2006 and 2009), and thematic data layers (roads and trail layers) for mapping wetlands in Mt. Rainier National Park. The spatial resolution of the LiDAR is 4-6 points per meter. The LiDAR vendor provided a canopy surface model, a digital terrain model, and an intensity image. In addition to the vendor-provided data we created additional data input layers using the LiDAR digital terrain model. From the digital terrain model we created a slope index at one meter pixel resolution. We used a D-infinity hydrologic flow model to create a flow accumulation model and a topographic wetness index (TWI). We chose the D-Infinity model over the more traditional D-8 hydrologic flow model available as part of hydrologic tools in ArcGIS because it is more suitable for braided channels, which are common in the subalpine regions of Mt. Rainier. Next, we identified sinks found within the digital terrain model using spatial analysis tools in ArcGIS. Identifying sinks is typically an intermediary step in any flow accumulation model to locate any areas that have an internal drainage. By subtracting the sink raster from the original digital terrain model we created a new data layer that identified the depth of the sink. Finally, we subtracted the canopy surface model from the digital terrain model to create a canopy height model.

In addition to the LiDAR derived data inputs we used a 2006 true color image and a 2009 false color image freely available through the National Agriculture Inventory Program. Finally, we added two thematic layers; park roads and park trails. All of the raster data was scaled to 1 meter and projected to the NAD 83 North UTM projection and uploaded into eCognition.

Wetland Classification

We developed a hierarchical classification mapping wetlands in two different related levels: wetland complexes and wetland components (ponds and wetland vegetation). To classify wetland components we first masked out all non-wetland areas. We mapped tree canopy using canopy surface model inputs and masked out roads and trails using thematic data layers provided by the park. Next we mapped streams using the flow accumulation models we created from the digital terrain model. We then mapped streams in areas with slopes less than 3 degrees as ponded streams. To map wetland ponds and wetland vegetation we ran a segmentation on the remaining pixels and classified objects using LiDAR intensity, depth of sinks, topographic wetness index, and both dates of aerial imagery. Additionally, for every date of imagery we used the spectral signature of deep water, taken from the center of deep ponds, to classify the deep and shallow water for every pond. For the 2008 LiDAR intensity imagery we classified deep water as regions of the pond where the water is deep enough to fully absorb the LiDAR. We exported out the wetland classification and descriptive statistics for each wetland complex and wetland pond.

Methods Comparison

We developed a second OBIA algorithm without using LiDAR-derived data inputs for the same area, Mt. Rainier National Park. We did this to compare the accuracy of adapting our method for areas without LiDAR data. Similar to the first algorithm we created hydrologic data products using a coarser 10 meter resolution digital elevation model (DEM). The 10 meter DEM was created by the USGS from 30 meter satellite imagery. We validated our classification outputs using data collected from 31 monitoring sites established in three areas of Mt. Rainier; Spray Park, Palisade Lakes, and Mazama Ridge.

Predicting Pond Drying Rate

We used the object statistics calculated on wetland complexes and their components, ponds and wetland vegetation, to determine if remote sensing variables could predict the slope of pond drawdown (i.e. percent change per each day during drawdown period). The slope of pond drawdown was derived from the field monitoring sites. We ran regression analysis using the descriptive statistics calculated from the input data layers; LiDAR intensity, depth of sinks, TWI, aerial imagery, slope index, flow accumulation model, digital terrain model, canopy height model, and the surface water area of the ponds as calculated for each date of imagery (2006, 2008, 2009) against the slope of pond drawdown.

Columbia Plateau Wetlands

The Columbia Plateau ecoregion is a semi-arid environment in the northwest of the United States. Isolated, depressional wetlands are the dominant wetland type in this ecoregion. Refill of wetlands in this area is typically driven by snowmelt occurring in late winter or early spring. As the summer season progresses temperature levels increase and precipitation levels decline. Wetlands begin to dry out during this time, with many wetlands completely dry by the end of the summer. Short-term rainfall events occur sporadically during the spring and summer months and are usually localized in nature. Although the direct causes of hydrologic change is not clear, wetlands in the Columbia Plateau are already stressed from impacts caused by farming, grazing, and reduced groundwater levels. It is still uncertain how these cumulative pressures will affect projected climate change impacts. Because there is no long-term landscape level hydrologic data for wetlands in this ecoregion it is difficult to determine the current condition and function of wetlands in the Columbia Plateau.

To reconstruct wetland hydrographs for all wetlands within our focal regions (Douglas County, Swanson Lakes Wildlife Area, and Turnbull Lakes National Wildlife Reserve) we used a two-step process using high resolution aerial imagery and a multi-date layer stack of Landsat satellite imagery spanning 27 years (1984 – 2011). A key objective was to create a product that could be used at multiple scales; from large landscape analysis to individual wetland monitoring, providing a tool for multi-scale resource management. For this method we relied on a technique called spectral mixture analysis (SMA), which identifies the fractional abundance of water within one Landsat pixel (J. B. Adams, Smith, & Johnson, 1986; Adams John B. & Gillespie, 2006).

Step 1: Wetland Delineation
We evaluated existing wetland inventories for all three focal areas and determined that the one for Douglas County was inadequate as it had high error of omissions and did not line up well with wetlands on the ground. Therefore, for Douglas County, we used object based image analysis of high resolution aerial imagery to create a new wetland inventory. Halabisky et al. (2009) provides a detailed explanation of this method. The wetland inventory in Swanson Lakes Wildlife Area had recently been re-done using OBIA techniques and was sufficient for our purposes. The National Wetland Inventory for Turnbull Lakes National Wildlife Reserve did not have errors of omission, but did not line up with wetland boundaries on the ground. We stretched and shifted the dataset to correct this issue. The wetland inventories for Swanson Lakes Wildlife Area and Turnbull Lakes National Wildlife Reserve were provided by local land managers. The resulting three datasets included delineated wetland polygons denoting the boundaries of individual wetlands.

Step 2: Reconstructing Surface Water Hydrographs
We used the delineated wetland polygons from each dataset to extract surface water estimates derived from spectral mixture analysis. To do so, we overlaid each wetland polygon over 331 Landsat satellite images spanning from 1984 – 2011 (the number of images available per site). For each data of imagery, we used SMA to identify the fractional abundance of water within each pixel within the polygon. Captured as a time series, we then used these results to reconstruct individual surface water hydrographs for 2,475 wetlands. Figure 2.1.2 provides an example of this two-step method. SMA results provide an estimate of surface water for each pixel within a wetland as well as a root mean square error, which demonstrates the fit of our SMA model. An RMS error with no distinguishable pattern suggests that the model represents all of the material components within a pixel and therefore accurately predicts surface water area for each pixel.

To validate our newly developed method we manually delineated surface water area for 100 randomly selected wetlands in Douglas County using high resolution NAIP imagery flown in 2011 spanning 2 days (July 6 – July 7). We compared the validation dataset to SMA surface water estimates derived from a Landsat satellite imagery acquired on July 7, 2011. We chose to focus validation on Douglas County because the aerial imagery flown in 2011 matched up with cloud-free satellite imagery. The surface water area of the validation dataset ranged from 0 (completely dry) to 22.48 hectares. Maximum wetland sizes of the validation dataset, derived from the Landsat time series dataset, ranged from 900 square meters to 32 hectares. We also attempted to validate results using temperature dataloggers (iButtons) to measure approximate water levels and wetland extent, and dates of ice-free open water in fifteen focal wetlands throughout the Columbia Plateau.

In addition to testing the accuracy of wetland area we wanted to understand the accuracy of percent changes to surface water area. To do this we relativized surface water estimates for each date of imagery by their maximum inundation, which provided an estimate of the percent surface water area for each wetland. We also used the same maximum surface area to relativize the reference dataset. We compared the percent surface water from the SMA to the reference dataset to calculate the difference in percent changes.

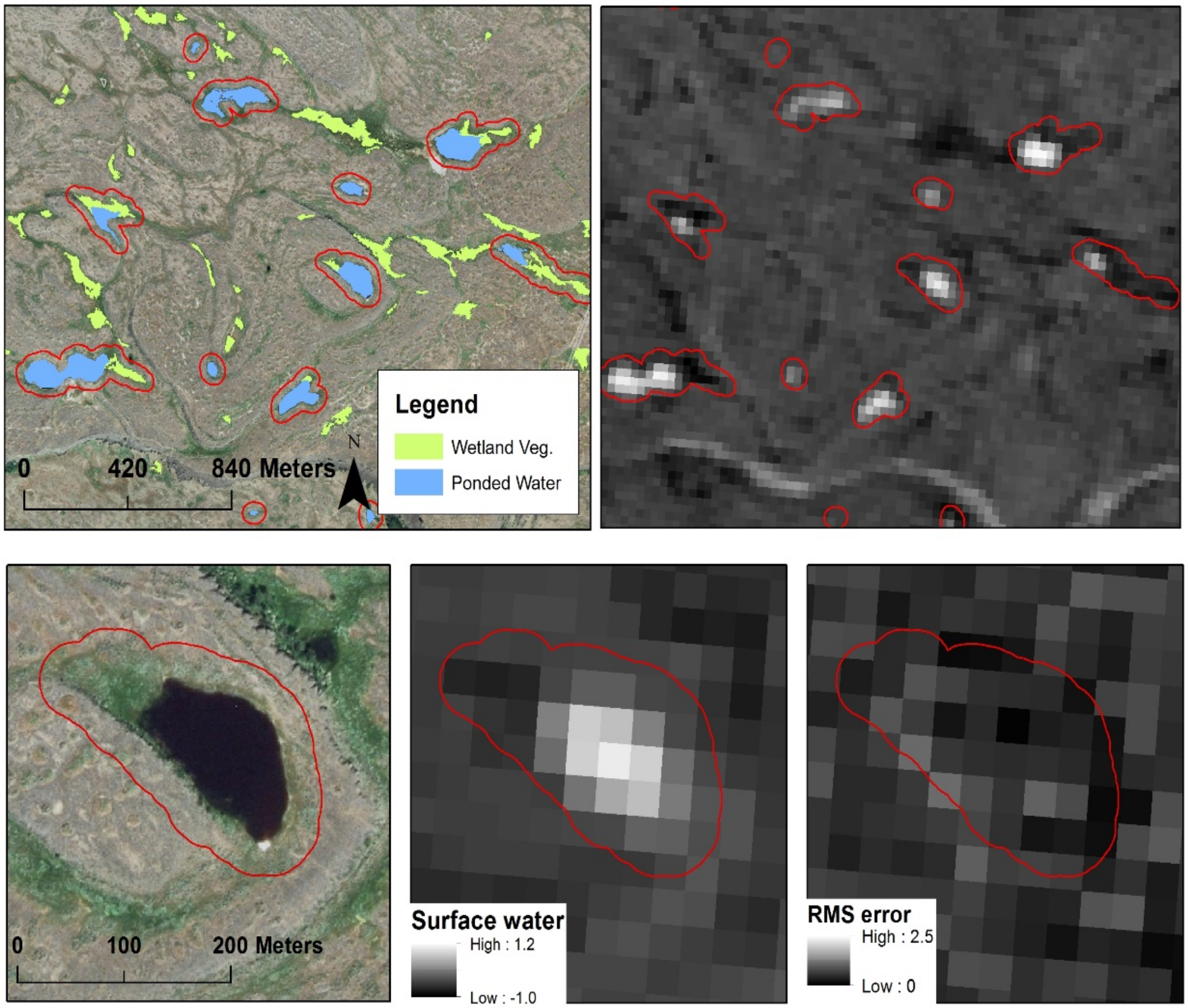


Figure 2.1.2: Example of combining high resolution classification using OBIA and surface water outputs from SMA. Wetland complexes, including pond and wetland vegetation were buffered by 30 meters (top left). SMA results (top right) were summed for each wetland polygon to derive surface water estimates for a given date. The example on the bottoms shows the SMA results, including the RMS error for one wetland, 3.4 hectares in size.

2.2 Monitoring of Focal Field Sites

We implemented field monitoring of wetlands in three regions of the Cascade and Olympic Ranges, the Columbia Plateau, and Puget Sound lowlands.

Montane wetlands

We completed three field seasons (2012, 2013, and 2014), collecting detailed data on wetland hydrology (pond depths and spatial extent) and amphibian occupancy and development across different geographic regions of Mount Rainier, North Cascades, and Olympic National Parks. We worked with National Park Service biologists and managers to select multiple regions within each Park with clusters of wetlands where we could monitor a broad range of wetland types, while also keeping field costs for multiple visits per year within budget. One region (Seven Lakes Basin) is also a US Geological Survey Amphibian Research and Monitoring Initiative (ARMI) long-term study site. While our sites are not a random sample, they represent a broad diversity of geographies and wetland types found within each Park.

Hydrologic monitoring

We monitored pond hydrology using three methods: 1) physical water depth monitoring conducted through repeated site visits (2-6) over the course of the summer and fall for years 2012 and 2013, 2) iButton temperature dataloggers to detect drying (2013-2014), 3) HOBO U20L water level dataloggers to capture high-resolution fluctuations in pond depth at select focal sites (2014).

For our primary dataset used in developing climate-hydrologic models, we collected detailed data on wetland hydrology (wetland depths and spatial extent) for 121 montane wetlands, representing a mix of ephemeral, intermediate, perennial, and permanent ponds, through physical monitoring. In a subset of wetlands, we also estimated wetland depths using iButton temperature dataloggers. To do so, we installed iButtons along transects from the edge of the wetland to the deepest accessible point in the wetland. We identified the date at which wetland water levels dropped below each iButton based on changes in the variance in temperature (measured every two hours). Because air temperatures fluctuate more dramatically than water temperatures, it is possible to compare temperatures of iButtons along each transect to iButtons placed in the open air adjacent to the wetland to determine when the iButton was submerged or exposed to the air. An example of iButton data from one transect is shown in Figure 2.2.1. Our physical depth measurements validated the estimates of water level derived from the iButton transects. This larger 2012 dataset supplemented several smaller historical

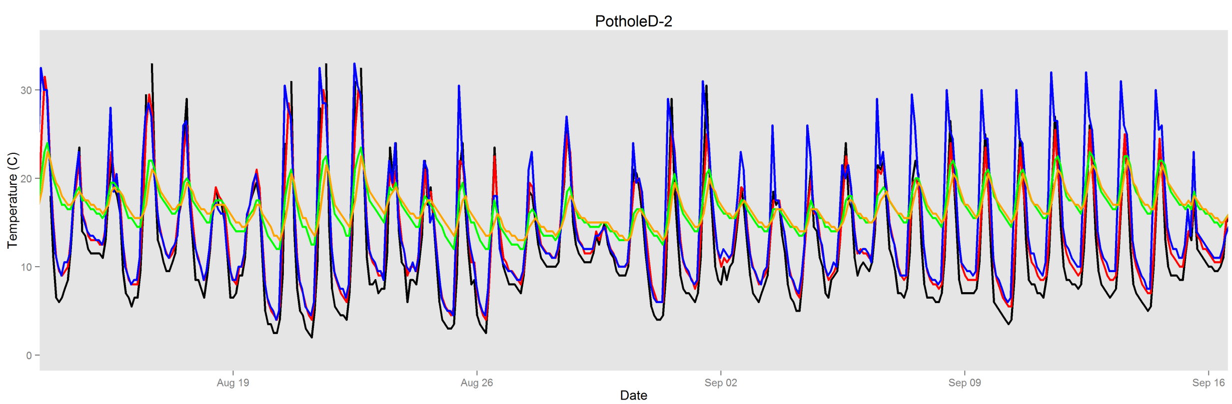


Figure 2.2.1. Water temperature data from an iButton transect in Pothole D in Olympic National Park. Each colored line represents an iButton placed at a different depth. The high-amplitude fluctuations are those of iButtons that dried, and lower-amplitude fluctuations are those that remained submerged (yellow, orange, and bright green), showing that Pothole D did not dry completely.

datasets that we also used in building the models described below. These included 1) measured wetland water depths for 7 montane wetlands in Seven Lakes Basin, Olympic National Park from the summer of 2000, 2) wetland water volume estimates for 10 montane wetlands on Mazama Ridge, Mount Rainier National Park from June through September 1992 (Girdner & Larson, 1995), and 3) multiple years of observed wetland depth data for one intermediate and two perennial wetlands in Oregon (Pearl, pers. comm.) and one intermediate wetland in California (Garwood, pers.comm.; Garwood & Welsh 2007). In total we used data from 125 wetlands in the modeling described below. All monitored or surveyed sites from 2012-2014 are listed in Appendix B. The HOBO data were not used in developing models because we do not yet have access to hydrologic model runs for 2014, but are an excellent resource for future research when updated VIC runs become available.

Amphibian monitoring: Sampling design, field surveys, and monitoring of breeding success
In the same suite of sites monitored for hydrologic change, we conducted amphibian visual encounter surveys in 2012 and 2013. Amphibian surveys focused on species presence and on key habitat attributes known or suspected to influence amphibian occupancy, habitat use (e.g. breeding versus foraging), and recruitment. We developed protocols in accordance with the US Geological Survey Amphibian Research and Monitoring Initiative's approach. We focused on three common montane species: *Rana cascadae* (Cascades frogs), *Ambystoma gracile* (northwestern salamanders), and *Ambystoma macrodactylum* (long-toed salamanders). We noted any additional pond-breeding amphibian species of any life stage where they were present (*Taricha granulosa,* rough-skinned newt; *Rana luteiventris,* Columbia spotted frog; *Pseudacris regilla*, Pacific chorus frog; *Bufo boreas*, Western toad).

To conduct visual encounter surveys, two-person teams carefully walked the perimeter of each pond and checked all microhabitats for amphibians (e.g. in the pond, under banks, stream inlets, in submerged or adjacent terrestrial vegetation) between 08:00 and 20:00 hours. During each survey, field crews recorded pond coordinates and the presence of any amphibian life stage (eggs, larvae or tadpoles, metamorphs, juveniles, terrestrial adults, paedomorphs, or dead animals of any stage). Crews also recorded habitat attributes that may be associated with amphibian occupancy, including elevation, pond dimensions (length and width to estimate circumference), depth, wetland type (lake, pond, or wet meadow), hydrologic class (ephemeral, intermediate, perennial, permanent), fish presence, percent shallows (flooded habitat <0.5m in depth), presence of emergent vegetation, substrate, presence of cobble, presence of downed wood, presence of complex side habitat, percentage of surrounding area that was wooded, and dominant types of emergent and riparian vegetation. Crews also recorded additional data on environmental factors that might further influence amphibian detection, including date, time of day, sky conditions, wind conditions, air temperature, water temperature, water presence, water depth, water color, water transparency, presence of predatory birds or snakes or invertebrates, and percentage of the pond perimeter successfully searched.

The seasonal start to surveys was determined by ice-out of the ponds, which we tracked carefully at the beginning of each season via communication with National Park Service rangers and field crew reconnaissance. In 2012, surveys began in late June and concluded in late October. We surveyed each site for the presence of amphibians between one and six times, with the majority of sites receiving three or four surveys. A subset of our sites is part of a long-term demographic study of *Rana cascadae*, and we surveyed these sites up to six times. In 2013 surveys began in July and ended in late September. In 2013, we conducted a smaller number of visual encounter surveys and focused on tracking developmental rates of *Rana cascadae* tadpoles and evidence of mortality as ponds dried. To do so, we staged tadpoles according to their Gosner stage, and noted any evidence of mortality (e.g. dried egg masses or dried tadpoles). In 2014 our field season began in June and ended in late September but we did not conduct visual encounter surveys and instead focused on intensively tracking *Rana cascadae* breeding effort and success, focusing on egg deposition, tadpole development, and tadpole survival or mortality in drying ponds. In all three years (2012-2014), we closely tracked developmental rates of *Rana cascadae* tadpoles and evidence of mortality of any species as ponds dried.

Columbia Plateau

Hydrologic monitoring

We placed over two hundred temperature dataloggers (iButtons) to measure approximate water levels and wetland extent, and dates of ice-free open water in fifteen focal wetlands throughout the Columbia Plateau. These dataloggers were placed in Fall 2012 and Spring of 2013. All of the iButtons in the Columbia Plateau were retrieved in Fall 2013.

Puget Sound Lowlands

Hydrologic monitoring

We monitored three ponds in the Puget Sound lowlands (Chuckanut Ridge, Bellingham region) using a combination of iButtons and physical measurements through the spring and summer of 2013. At two sites, iButton transects were disturbed by animals (humans and mink), disrupting data collection. Through outreach to collaborators Michele Bodkhe and Victoria Jackson of Northwest Ecological Services, we identified an existing dataset (collected biweekly from December 2005 to November 2006) for seven wells in four wetland complexes (ponds and saturated wetland areas) in the same region, and used those data in place of the iButton data. This is an improvement over our original plan, since VIC simulations are only available currently in our region through 2012, so the data we were collecting would not have been useful in testing and calibrating the VIC model for Puget lowland sites until future years. With our collaborators' dataset we were able to test and calibrate the VIC using existing simulations.

2.3 Climate-Hydrologic Modeling

Montane Wetlands

In previous work under our North Pacific Landscape Conservation Cooperative grant, we developed methods for projecting climate-induced hydrologic changes for montane wetlands in Washington, Oregon, and California by using regression models that related observed wetland water levels to the best predictor among simulations of ecologically relevant water balance variables (such as precipitation, soil moisture, runoff, baseflow, and evapotranspiration) from the Variable Infiltration Capacity (VIC) macroscale hydrologic model implemented at 1/16th degree resolution (Elsner et al., 2010, Hamlet et al., 2013). In this project, we extended and refined this previous work using newly collected, more extensive hydrologic datasets collected a) in focal field sites in the mountains and b) from remote sensing-derived data in the Columbia Plateau, described above. For montane regions, we also developed the relationship between the slope of pond drawdown (i.e. percent change per each day during the drawdown period) and pond drying or minimum water level of ponds to classify the wetland type and evaluate shifts in the distribution of wetland types under climate change.

The additional year of data on wetland hydrology (from 2012) allowed us to better characterize inter-annual hydrologic variation in response to climate and evaluate the ability of the VIC model to capture this important form of variation. A description of the complete suite of approaches is described below (from Lee et al. *in review*).

Wetland classification

We define wetlands broadly as any area where shallow surface water collects. Wetlands exist on a hydrologic continuum and many different methods of wetland classification exist (e.g. Cowardin, hydrogeomorphic or HGM). We use a simple hydrologic classification scheme based on hydroperiod and wetland sensitivity to climate variability to characterize four ecologically relevant types of wetlands – ephemeral, intermediate, perennial, and permanent (Table 2.3.1). This approach relates inherently continuous hydrologic variation in water permanence and periodicity to more discrete ecological thresholds determined by species' development and life history requirements (e.g. number of months or years that ponds must hold water for an insect, frog, or salamander to develop and metamorphose) (Girdner & Larson 1995, Tarr & Babbitt 2008).

Table 2.3.1. Hydrologic Classification of Montane Wetland Types

Wetland Classification	Hydrologic Characteristics	Ecosystem Characteristics
Ephemeral	Ephemeral or short-hydroperiod wetlands dry in most years, in some cases soon after the cessation of snowmelt or seasonal rains.	Ephemeral montane wetlands are not used by many animals due to their extremely brief inundation, but may support wetland plants.
Intermediate	Intermediate-hydroperiod wetlands tend to dry in late summer or early fall in years with low precipitation. During relatively wet years, they hold water year-round. Water levels fluctuate considerably in summer.	Intermediate-hydroperiod wetlands support populations of fast-developing amphibians, invertebrates with resting egg stages that can survive desiccation, migratory birds, mesopredators, and wetland-obligate plants.
Perennial	Perennial wetlands do not dry except in the most extreme dry years, but often lose a substantial percentage of their volume during dry periods.	Perennial wetlands often support the greatest diversity and abundance of amphibians and invertebrates, including fast-developing species and those that require multiple years to complete larval development in high elevation environments, while lacking predators such as introduced fish that often reduce species diversity (Bahls 1992). Wetland-obligate plants, birds, and mesopredators, may also rely on perennial wetlands.
Permanent	Permanent wetlands do not dry	Permanent wetlands support a broad range

and lose a relatively small percentage of their volume even during unusually dry periods.

of mammals and birds, and can be used by the full suite of wetland-breeding amphibians and most invertebrates, though increased predation (by native and introduced predators) limits actual occupancy. Primary poductivity depends in part on the amount of shallow littoral habitat. Wetland macrophytes are common.

Quantitatively we define the four wetland types based on average minimum water levels. Generally shallow **ephemeral wetlands** dry completely or drop, on average, below 3% of their maximum water levels. **Intermediate wetlands** drop to between 3% and 33% of their maximum water levels on average and may dry in some years. **Perennial wetlands** drop to a mean of 33% to 70% of their maximum water levels and only in extreme droughts do they dry completely. For **permanent wetlands** (lakes and large ponds), the average minimum water levels generally remain greater than 70% of their maximum water levels and are never dry in the historical record. These four types represent general hydrologic classes of wetlands that can be related to more detailed hydrogeomorphic wetland-classification systems such as those used in U.S. Natural Heritage programs and for conservation decision making (WDNR 2011; Hruby 2006).

Observed wetland data

Observed wetland data collection is described in Section 2.2 above. Regions of study used in the montane wetland analysis are depicted in Figure. 2.3.1. Figure 2.3.2 shows focal field sites with multiple years of hydrologic data. All sites used for hydrologic modeling are listed in Table 2.3.2.

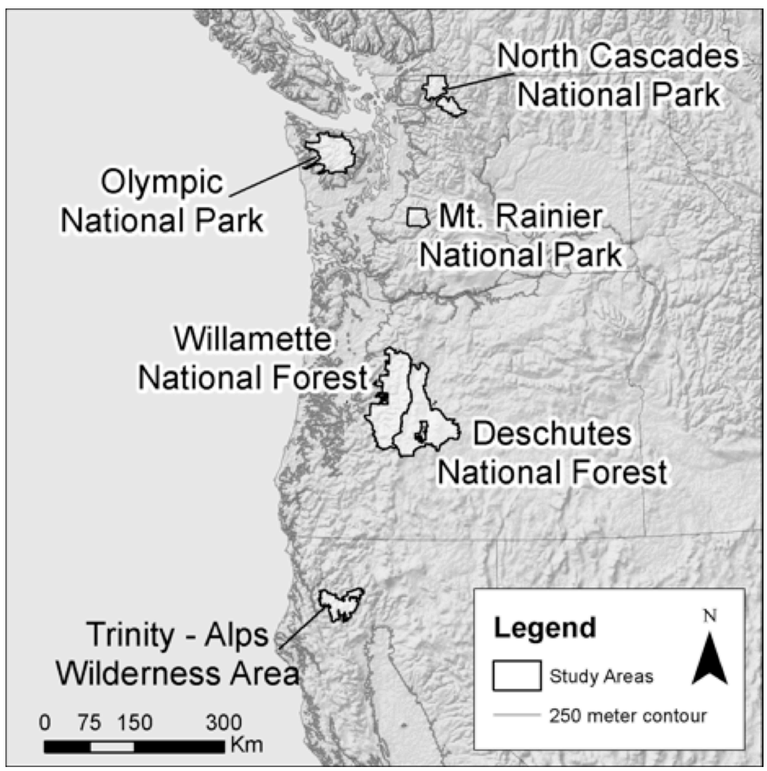


Figure 2.3.1. Regions with observed wetland data used to calibrate montane wetland models.

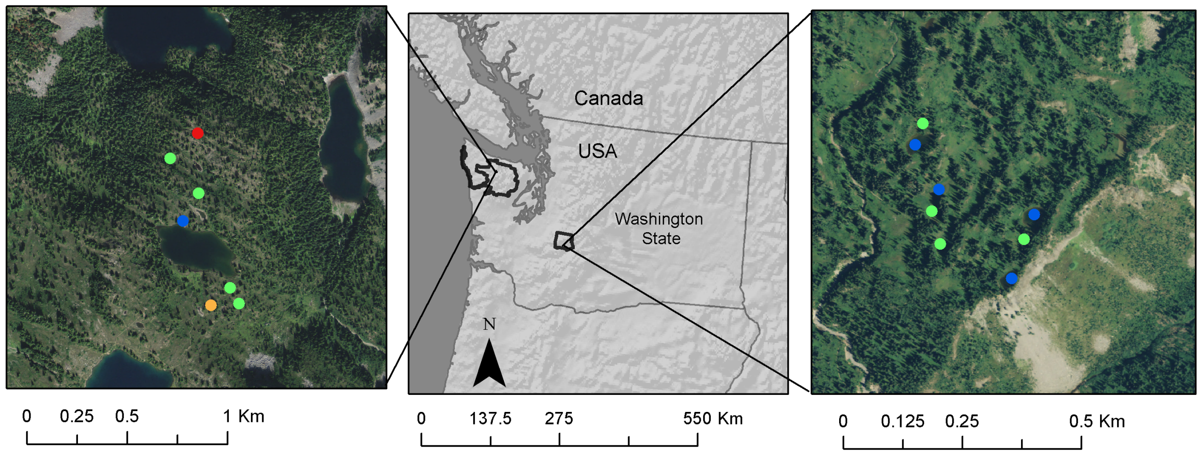


Figure 2.3.2. Locations of a selection of focal field sites in Seven Lakes Basin in Olympic National Park (left) and Mazama Ridge/High Lakes in Mount Rainier National Park (right) with multiple years of hydrologic data. Points indicate the pond type: red is ephemeral, orange is intermediate, green is perennial, and blue is permanent.

Table 2.3.2. Summary of observed wetland data used in montane wetland climate-hydrologic modeling.

	Type	Period	Number of Wetlands				Data Source
			Ephemeral	Intermediate	Perennial	Permanent	
Mt. Rainier National Park, WA	Vol.	Year 1992	–	–	5	5	Girdner & Larson (1995)
	Depth	Year 2012	4	9	4	13	Field Measurement, M. Ryan
			2	–	2	1	iButton, M. Ryan
Olympic National Park, WA	Depth	Year 2000	1	–	4	1	Field data, W. Palen
		Year 2012	17	19	20	21	Field Measurement, M. Ryan
			1	–	4	–	iButton, M. Ryan
North Cascades National Park, WA	Depth	Year 2012	2	–	–	1	Field Measurement, M. Ryan
			–	–	–	1	iButton, M. Ryan
Willamette National Forest, OR	Depth	Years 2003-2006	–	1	1	–	Field Measurement, C. Pearl
Deschutes National Forest, OR	Depth	Year 2003 & 2006	–	–	1	–	Field Measurement, C. Pearl
Trinity Alps Wilderness, CA	Depth	Years 2003 – 2007	–	1	–	–	Field Measurement, J. Garwood

Macro-scale hydrologic model

To hindcast over a large number of retrospective years and to project climate-induced hydrologic change, we used the macro-scale Variable Infiltration Capacity (VIC) hydrologic model (Cherkauer *et al*. 2003; Liang *et al*. 1994), implemented at 1/16th degree resolution (roughly 5 km by 7 km) over the Pacific Northwest (PNW) and California (CA). The PNW model implementation, historical simulations, and climate change scenarios are described in detail by Elsner *et al*. (2010), Hamlet *et al*. (2013), and Tohver *et al*. (2014). The VIC model implementation over the western U.S. is described by Salathé *et al*. (2013). For given input data including temperature, precipitation, wind, vapor pressure, net incoming longwave and shortwave radiation, and air pressure, the VIC hydrological model simulates water balance variables such as snowpack, soil moisture, evapotranspiration, runoff, baseflow and soil moisture in three soil layers comprising the first several meters of soil. Simulations at each VIC grid cell cover an extended historical time period (water-years (i.e. October 1 to September 30) 1916 – 2012 for the PNW and 1916 – 2010 for California). We used these water balance variables to develop empirical regression models of wetland response as described below and to hindcast historical variability of water levels in wetlands over 97 (PNW) and 95 years (CA) (Fig. 2.3.3).

Regression models of wetland water levels

As a first step, we used the correlation coefficient (Pearson's R) to identify the strongest relationships between observed wetland water level at each site and a suite of water balance variables including precipitation, evaporation, runoff, snow-water equivalent, and simulated soil moisture in the three different layers. Secondly, we constructed empirical models of wetland response by fitting regression equations to observed wetland volumes or depths using the best-correlated water balance variable. Because montane wetlands are relatively undisturbed by human changes in land use, when making future projections, we assumed that the fitted regression relationships between wetland response and the soil moisture of the best-correlated water balance variable will not change with time. We developed a regression model using only observed data during drawdown periods because we did not have enough observed data during the rapid refill seasons to develop robust regression models for these. Also, for this system, the ecological consequences of altered timing of wetland drawdown and drying are greater than shifting timing of wetland refill, so we focused on the drawdown cycle for this reason as well.

For most Mount Rainier, Olympic, and North Cascades sites, we had only a single year of data from which to fit the regression models. However, when multiple-years of observations were available (e.g. for some sites in Mount Rainier and Olympic National Park and for all sites in Oregon and California), we investigated the uncertainty in the projections when fitting to a single year of data. For Oregon and California sites that showed similar gradual drawdown patterns for observed years, we fitted a separate regression model for each individual year of multiple-years of observations, developed simulations for all years using each of these models, and then calculated the squared correlation coefficient (R^2) using all observations and the corresponding simulations for each model. We then used the single-year regression model showing the highest squared correlation coefficient (R^2) for all the available data to simulate historical wetland response and the associated climate-change response. We used the regression models fitted to other years to estimate the uncertainty in the simulations due to uncertainty in the regression parameters for individual years. For the Willamette National Forest site, for example, the squared correlation coefficient (R^2) for the three regression models was 0.49, 0.88 and 0.75 for 2003, 2005 and 2006 data, respectively. Therefore, we used the regression model fitted on the 2005 observed data to simulate the historical response and used the regression models for years 2003 and 2006 to estimate the uncertainty of the simulation due to uncertainty in the regression fit.

The Mount Rainier and Olympic National Park sites with two years of observed data presented somewhat different drawdown patterns between years in response to different weather conditions. For example, one site in ONP showed gradual drawdown for year 2012 but intermittent drawdown and frequent partial refill events for 2000. Thus, we developed a regression model using the earlier year's data (e.g. 2000 data for Olympic National Park and 1992 for Mount Rainier), which had a greater number of observations and showed more dynamic changes in water levels. We then used the 2012 data from both regions to validate the regression models in the context of potentially different patterns of drawdown and refill across years.

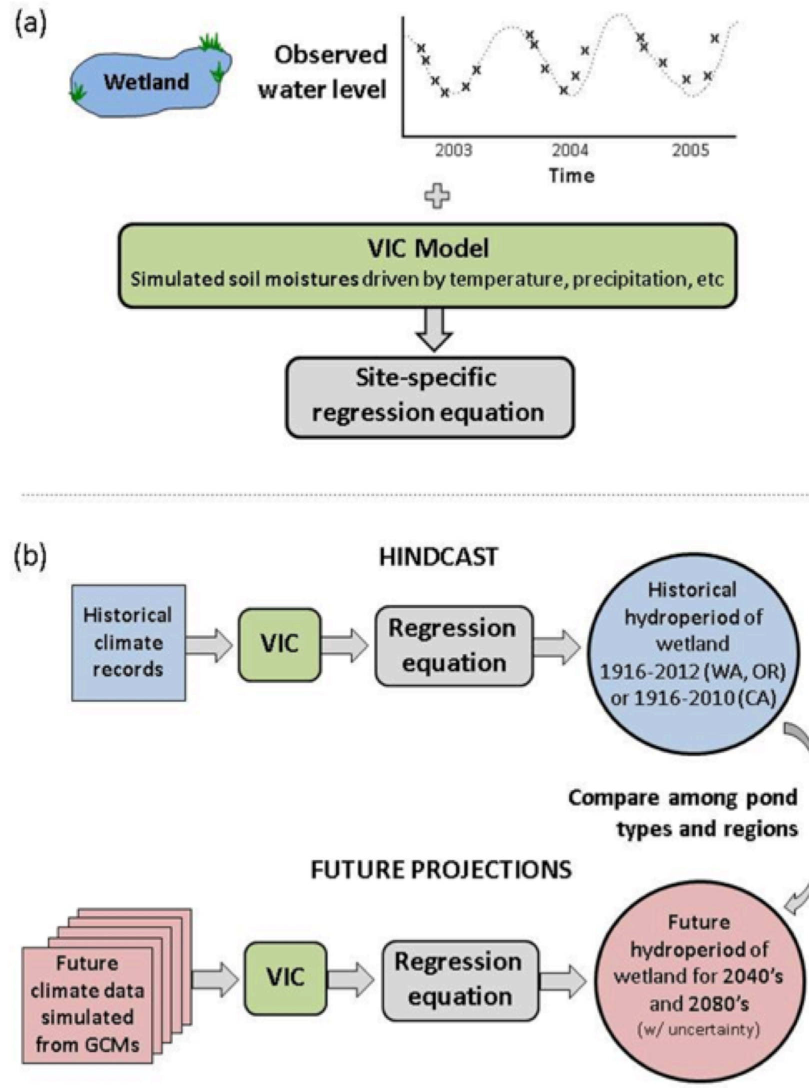


Figure 2.3.3. Schematic diagram of the method of projecting and hindcasting wetland hydrology using the VIC hydrologic model calibrated with empirical data and driven by historical or simulated future climate impacts.

Climate change scenarios

To simulate potential future changes in water dynamics of individual montane wetlands in the PNW, we used simulated climate from the ECHAM5 general circulation model (GCM) forced by the A1B emissions scenario, which approximates the average conditions simulated for the region by ten different GCMs forced by the same emissions scenario. Climate projections were downscaled with the Hybrid Delta (HD) method described in detail in Appendix A of Tohver *et* *al*. (2014). Briefly, the HD method uses quantile mapping techniques to produce the transformed monthly observed climate data (years 1916-2006; a 91-year time series) in response to 30 years of monthly GCM projections for two future time periods: the 2040s (2030 – 2059) and the 2080s (2070 – 2099), producing 91 years of future inputs for the VIC model. The future monthly values are then used to rescale the daily values from the *observed* month to produce a future daily time series. As a result, the HD approach provides 91 years of observed variability ("1916-2006") for each future time period, and is directly comparable to the historical record on an event basis from 1916-2006. Note that for historical runs we extended the VIC runs from 1916-2006 to 1916–2012 in order to use field data obtained in 2012. However, for climate scenarios we used existing data developed by Hamlet *et al*. (2013) that have 91 years of observed variability, projected for future time periods. For landscape scale projections of the probability of drying for intermediate wetlands in Washington, we used an ensemble of ten climate change projections from 10 different global climate models based A1B scenarios (Hamlet *et al*., 2013). We report the average of these results.

For California, we used the ECHAM5 A1B scenario based on the Distributed Delta (DD) downscaling approach that is described by Littell *et al*. (2011) and Salathé *et al*. (2013). Although, ideally, we would have used data downscaled with the same approach for the California sites as we did for the Oregon and Washington sites, these data were the ones readily available from previous studies. Similar to the HD approach, the DD scenarios construct a 95-year time series for two future time periods, which have the same number of years as the observations used in the downscaling. Although there are some differences in details between this downscaling method and the HD approach described above (e.g. length of record, method by which the changes in climate are applied to the historical time series), for our use here these differences are not particularly important. Both methods incorporate the spatial distribution of temperature and precipitation changes from GCMs, and changes in the central tendency of projected temperature and precipitation in each region are similar in each case.

Historical reconstruction, future projections, and frequency analysis of wetland dynamics
We estimated the average minimum wetland water level for both the historical runs and two future scenarios with time series behavior derived from the historical period. The average minimum wetland water levels were used to classify wetland types and evaluate the impacts of climate change on minimum wetland water levels.

To project changes in the distribution and behavior of wetlands at landscape scales, we investigated a threshold for wetland drying (when ponds reach 0% of maximum water level) that can be applied generally across different locations and soil types. To do so, we evaluated the relationship between wetland drying and “field capacity.” Field capacity is the volumetric soil water content of soil that is partly saturated, but drains very slowly by gravity. This metric relates directly to our best predictors (soil moistures, as discussed below). We converted absolute soil moisture values generated by the VIC model to the field capacities that vary with soil type. We then compared simulated soil moisture with wetland water levels for ephemeral and intermediate wetlands at Mount Rainier and Olympic National Parks to find a threshold below which wetlands tend to dry out. Finally, we used the mean threshold of drying across regions and soil types as a proxy for intermediate wetland drying for each VIC grid cell in the landscape scale analysis.
To calculate the probability of drying in each cell we counted the number of water-years for which the magnitude of soil moisture in the bottom soil layer was less than the drying threshold, and then divided by the total number of water-years. Thus the probability of wetland drying

ranges from 0 to 1, with a higher value indicating more frequent wetland drying. We calculated the probability of wetland drying for the historical run and for all ten Hybrid Delta A1B scenarios for the 2080s, averaging the latter results for presentation in the plots. We then estimated the change in the probability of wetland drying by subtracting the probability of wetland drying for the historical run from that for the average value for the 2080s, with a positive value indicating an increase in the probability of drying for the 2080s.

Water temperature modeling
We collected water temperature data for 18 montane wetlands using iButtons during the summers of 2012-2013. We developed regression models based on the relationship between observed 2012 water temperature and simulated air temperature. (Simulated air temperature is not available for 2013.) We then used these regression models to project changes in water temperature under climate change scenario A1B.

Puget Lowlands Wetlands
We applied the same methods as for montane wetlands to develop an empirical regression model for each wetland in the Puget lowlands. Briefly, we selected the best predictor among the ecologically relevant water balance variables (such as precipitation, runoff, baseflow, snow-water equivalent, evapotranspiration, and simulated soil moisture in the three different layers) simulated by the Variable Infiltration Capacity (VIC) macroscale hydrologic model, implemented at 1/16th degree resolution (Elsner et al., 2010, Hamlet et al., 2013). We then developed a site-specific regression model using observed wetland water depth and the best predictor. We used the empirical regression model for each site to hindcast historical wetland water depth (water years 1916-2012) and project the impacts of climate change on wetland hydrology using ECHAM5 global climate model scenarios for the 2040s and 2080s (A1B emissions scenario) (Hamlet et al., 2013). We averaged annual minimum water depth for both the historical period and for climate change. The average minimum wetland water depth for the historical run was used to classify wetland types following the same classification scheme developed for montane wetlands above. We then compared the average minimum water level under climate change with simulated historical water levels to assess the impacts of climate change on minimum wetland water levels. The dataset contributed by Michele Bodkhe and Victoria Jackson of Northwest Ecological Services is described in Table 2.3.3.

Table 2.3.3. Summary of observed wetland data obtained from monitoring of focal sites for Puget Lowlands wetlands.

Location	Type	Period	Wetland Types	Number of Wetlands	Data Source
Puget Lowlands	Depth	Dec. 2005 - Nov. 2006	Ephemeral	3	Field data, M. Bodkhe and V. Jackson (Northwest Ecological Services)
			Intermediate	3	
			Perennial	1	

Columbia Plateau Wetlands
The remote sensing technique described above was applied to reconstruct the historical surface area of wetlands in the Columbia Plateau from 1984-2011. This yielded high-quality datasets of historical observations for 772 wetlands: 410 in Douglas County, 279 in Swanson Lakes, and 83 in Turnbull Lakes (Table 2.3.4).

Table 2.3.4. Summary of observed wetland data obtained from remote-sensing for Columbia Plateau wetlands.

Location	Type	Period	Number of Wetlands	Data Source
Douglas County	Surface Area	Years 1984-2011	410	Remote-Sensing Measurement, M. Halabisky
Swanson Lakes			279	
Turnbull Lakes			83	

Because multiple years of observations covering both the refill and drawdown seasons were available from the remotely sensed dataset, we applied a similar but modified approach to the one used for montane wetlands. First, we divided all 27 years of wetland hydrologic data into calibration (1996-2011) and validation (1984-1995) periods. The calibration and validation periods were chosen in chronological order to include a range of climate variability with which to test the performance of regression models in reproducing historical patterns. Next, we developed multivariate regression models to cover both the refill and drawdown seasons. To develop the multivariate regression models, we selected from among all water related variables the two variables that were best correlated with remotely sensed observations. (Note that this differs from the single regression model with one predictor used above to reconstruct historical patterns during only the drawdown season.) Finally, we calculated Nash Sutcliffe efficiency (NSE) as well as the Pearson's R value as measures of goodness of fit.

Unlike our montane sites, we have limited on-the-ground data with which to hydrologically classify Columbia Plateau wetlands a priori based on mechanistic drivers of hydrologic patterns. Also unlike the montane sites, the Columbia Plateau is a region of complex and potentially strong human influences on hydrology. Therefore, for both reasons, our approach requires an additional step of data exploration and hypothesis development, and our classifications should be understood as hypotheses to be further explored and tested (stemming from observed model relationships), rather than mechanistically-based classifications in which we can be strongly confident.

Based on model fit to the observed data, we classified the wetlands into four groups. When the multivariate regression models reasonably reproduced observed daily historical patterns (Group 1 in Figure 2.3.4), we used these models to hindcast historical wetland behavior in response to observed climate variability for the historical period (1916 to 2012) and to project changes in wetland hydrology corresponding to projected changes in climate. We estimated the impacts of climate change on wetland hydrology by comparing annual minimum water levels simulated for the historical period and for climate change. For wetlands that did not fit with multivariate regression models, we tested whether wetland hydrology alternatively corresponded well with cool season (October to March) precipitation by developing regression models using cool season precipitation and annual mininum water level observations. For the group where the regression with cool precipitation data was a good fit (Group 2 in Figure 2.3.4), we explored whether these wetlands were more strongly fed by groundwater, as a potential mechanism to explain the different hydrologic behavior of these sites. We did so by comparing the locations of Group2 wetlands with available on-the-ground hydrologic data. For Group2 wetlands, we also used the regression model with cool season precipitation to produce annual minimum wetland surface area for the historical runs and for climate change.

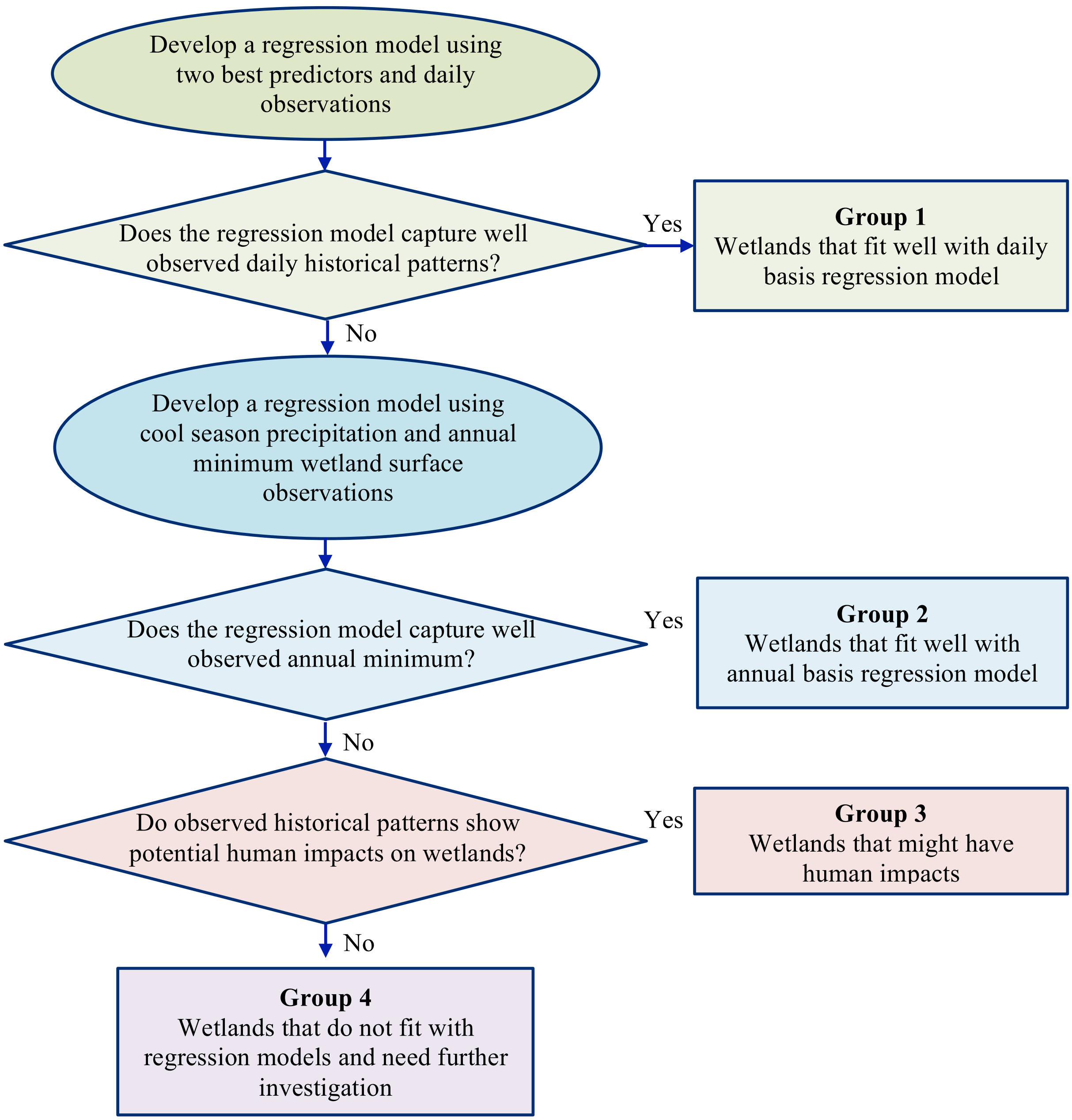


Figure 2.3.4. Schematic diagram of classifying four groups of wetlands in Columbia Plateau.

For wetlands that did not fit well with either multivariate regression models using the two best overall predictors nor regression models using cool season precipitation, we investigated whether hydrologic patterns might indicate anthropogenic disruption. For example, we investigated whether hydrographs showed substantial changes in pattern over time, such as switches or step changes among unusually high or low values relative to other periods. In comparison with montane sites, the Columbia Plateau has many complex human influences on the movement of water across and through landscapes, so we would expect these effects to be evident in some hydrographs. If wetlands showed sudden unexpected changes that suggested some form of active disturbance, we classfied those as likely human impacted wetlands (Group 3 in Figure 2.3.4). Group 4 are the wetlands that we could not confidently classify into any of above groups, and which need further investigation.

2.4 Ecological Modeling

Montane Wetlands

Analysis of Pond-breeding Amphibian Habitat Use

We used amphibian visual encounter survey data from 2012 to relate amphibian presence and habitat use (breeding or adult/foraging) to our four hydrologic wetland classes and other habitat attributes. We focus on the three common focal species for which we have sufficient data for a meaningful analysis: *Rana cascadae, Ambystoma macrodactylum, and Ambystoma gracile*. Because we anticipate that some species use different habitats for breeding versus foraging, we analyzed our dataset in two ways, first looking at the presence of life stages that indicate breeding (eggs, larvae, and tadpoles), and second at the presence of adult stages of each species.

Using survey data, we constructed binomial logistic regression models to predict binary presence or absence of a) breeding evidence or b) adult life stages (terrestrial or aquatic) for the three focal species from the 2012 dataset. Included in the analysis were individual ponds (n = 219) that we visited from 1 to 5 times each over the course of the breeding season. If we detected breeding efforts (egg masses or larval life stages) during any of those visits, this was coded as positive evidence of breeding. Our explanatory variables represent a suite of hydrologic and habitat variables: pond elevation (m), maximum pond size (circumference in m^2), maximum pond depth (m), pond hydroperiod (ordered factor, 4 levels: ephemeral, intermediate, perennial, permanent), presence of fish in the pond (binary factor), maximum percent of the pond that was shallows (<0.5m) during the breeding season, maximum percent of the pond occupied by emergent vegetation throughout the breeding season, presence of complex adjacent habitat that may be used by amphibians (binary factor), percent of the pond perimeter occupied by woods, substrate class (factor, 4 levels: muck, mud/clay/silt, sand/gravel, cobble/boulder), presence of cobbles in the substrate (binary factor), and presence of dead wood in the pond (binary factor). We examined all combinations of explanatory variables to test for co-variation and used principal component analysis (PCA) where necessary to transform strongly correlated variables into uncorrelated variables (PCA axes) for analysis. Due to the variety of survey efforts and types across the ponds, some ponds had to be dropped from the analysis due to data paucity, producing a smaller subset of ponds on which the analysis was performed (n = 169).

In order to avoid over-fitting, we limited the number of parameters included in models to 5 (including intercept; Burnham, Anderson 2002). We used Akaike's Information Criterion (Akaike 1974) to compare the degree of support for all combinations of 5-parameter models. This approach is generally used to explore data in the absence of any *a priori* hypothesis being considered more or less probable (Anderson, Burnham 2002). While we strongly suspected that hydroperiod and the presence of fish would be important drivers of amphibian adult presence and breeding, we used this approach to explore the data given the uncertain effects of most other variables (Symonds, Moussalli 2011). The results of this method can then be used to inform more traditional hypothesis tests, which we are conducting now and are a more appropriate way to check for interactions among parameters. These will be reported in future publications.

We performed analyses using *R* (v 3.0.2; R Core Team 2013), with the AIC analysis package *AICcmodavg* (Mazerolle 2013). We calculated Akaike weights (w_{Ak}) for each model (weight of support between 0 and 1, all w_{Ak} sum to 1), which can be interpreted as the probability that a given model is the best approximation (Symonds, Moussalli 2011). To estimate a 95% confidence set of models (a subset of candidate models that we are 95% sure contains the best model in the original set), we selected the top models whose cumulative w_{Ak} just surpassed 0.95 (Burnham, Anderson 2002). To compare the relative importance of individual variables, w_{Ak} for all models containing each variable were summed, resulting in a relative ranking of variable importance. The w_{Ak} was also used to calculate the weighted mean of variable coefficients across all models in which each variable was included. For visual ease of interpretation, we scaled and centered all variables (mean of 1, standard deviation of 1) so that their coefficient estimates are directly comparable and relative to their importance.

We are currently exploring these data with a number of additional approaches not reported here. Occupancy analyses are a common approach to amphibian habitat association studies, because they make it possible to estimate detection rates as well as species occupancy, thereby accounting for false absences in the data. Our dataset presents several challenges for occupancy analyses given the particular focus of our study. Most significantly, we are most interested in the relationship between hydrologic dynamics, species habitat use, and breeding success. However, due to the mechanics of occupancy modeling, sites that dry must be dropped from the analysis once dry. 2012 was a climate change analog year, hence many of our sites dried, which presents a number of methodological and interpretive challenges for the analysis. Therefore, for the initial hydrologic assessments that are the focus of this study (i.e. to identify core relationships between species habitat use and pond hydrologic types), we use the methods described above, but moving forward are further exploring the use of occupancy analysis to estimate variation in detection in relation to a range of habitat attributes that are shared among different hydrologic classes. We discuss additional analyses under "Next Steps" below.

2.5 Synthesis

Montane Wetlands

Synthesis of Climate-Hydrologic Models with Ecological Analyses

We evaluated the vulnerability to future climate impacts of our three focal species of pond-breeding amphibians (*Rana cascadae, Ambystoma macrodactylum, Ambystoma gracile*). Because these three species represent different life history and developmental requirements in the Cascade and Olympic mountains, we hypothesized that this variation would be associated with differential use of wetland habitats and therefore different levels of risk of climate-associated habitat loss.

Vulnerability to climate impacts combines sensitivity, exposure, and adaptive capacity (Glick et al. 2011). Sensitivity is a measure of whether or how a species or ecosystem is likely to be affected by climate change based on its biology and physiology (if a species) or other factors such as geographic location and associated processes (if an ecosystem). Exposure is the intensity of climate change impacts a species or ecosystem is likely to experience given where it lives or is located. Adaptive capacity is the range of ways a species or system might be buffered from climate impacts to reduce its sensitivity or exposure and enable it to cope without significant changes in viability or ecological function. Adaptive capacity includes biological responses such as migration, behavioral changes, or evolutionary adaptation. Also, in a management sense, adaptive capacity refers to opportunities to actively ameliorate impacts through conservation actions (Glick et al 2011).

We assessed sensitivity to climate change based on the strength of association of each focal species with the four wetland hydrologic classes, as determined by the ecological analyses above, and in relation to the relative vulnerability of each class of wetland to climate change, as determined by the climate-hydrologic models of future impacts.

To assess exposure, we overlaid the VIC hydrologic output maps showing changes in wetland drying rates by the 2080s with National Wetland Inventory hydrologic water regime modifier cross-walked to our wetland hydrologic classification. For example, we classified all wetlands with the NWI hydrologic modifier defined as "seasonally flooded" as intermediate wetlands. Seasonally flooded wetlands are defined as having "surface water present for extended periods especially early in the growing season, but absent by the end of the growing season in most years". See Appendix C for a detailed explanation of the NWI hydrologic modifiers and how they relate to our pond classifications. While the NWI is imperfect, this approach enables us to 1) relate the proportion of available habitats of different types within each VIC grid cell to projected changes in the level of climate-induced hydrologic risk, and 2) estimate changes in the distribution of wetland types within each VIC geographic cell by extrapolating from our focal site assessment of the proportion of ponds that will switch categories under future climates. We are in the process of conducting a separate analysis of Mount Rainier National Park where improved wetland mapping resources are available, not reported here.

Finally, to assess adaptive capacity, we assess management-related adaptive capacity by identifying regions where introduced fish are present and could potentially be removed as a means of restoring what appears to be more climate-resistant wetland habitat for amphibians (Ryan et al. 2014). Relatively little is known regarding biological responses of our three primary species to climate change. What information is available we discuss below.

3. Project Results

3.1 Remote-Sensing of Wetlands

Montane Wetlands

Our method using object based image analysis of high resolution imagery and LiDAR mapped substantially more wetlands than the National Wetland Inventory (NWI) and produced a finer, more accurate wetland delineation (Figure 3.1.1). When compared to the 31 groundtruthed wetland monitoring sites in Mount Rainier National Park, our classification using LiDAR data and high resolution imagery had an accuracy of 90.3% (Table 3.1.1). Two of the three sites that were not mapped as wetland ponds were mapped as streams. The site that was missed was too small and ephemeral to be detected through visual assessment of all data inputs. The NWI mapped only 61.3% of the sites. Additionally, the NWI dataset had offset errors, where the delineations were slightly offset from the actual wetland locations (Figure 3.1.1). Additionally, through hydrologic flow modeling we were able to map small stream locations as well as wetland vegetation. Figure 3.1.1 shows a comparison of our classification using LiDAR and the NWI.

Object based image analysis using digital elevation models with a 10 meter pixel resolution did not produce useful results. This classification mapped only 58.1% of the wetland

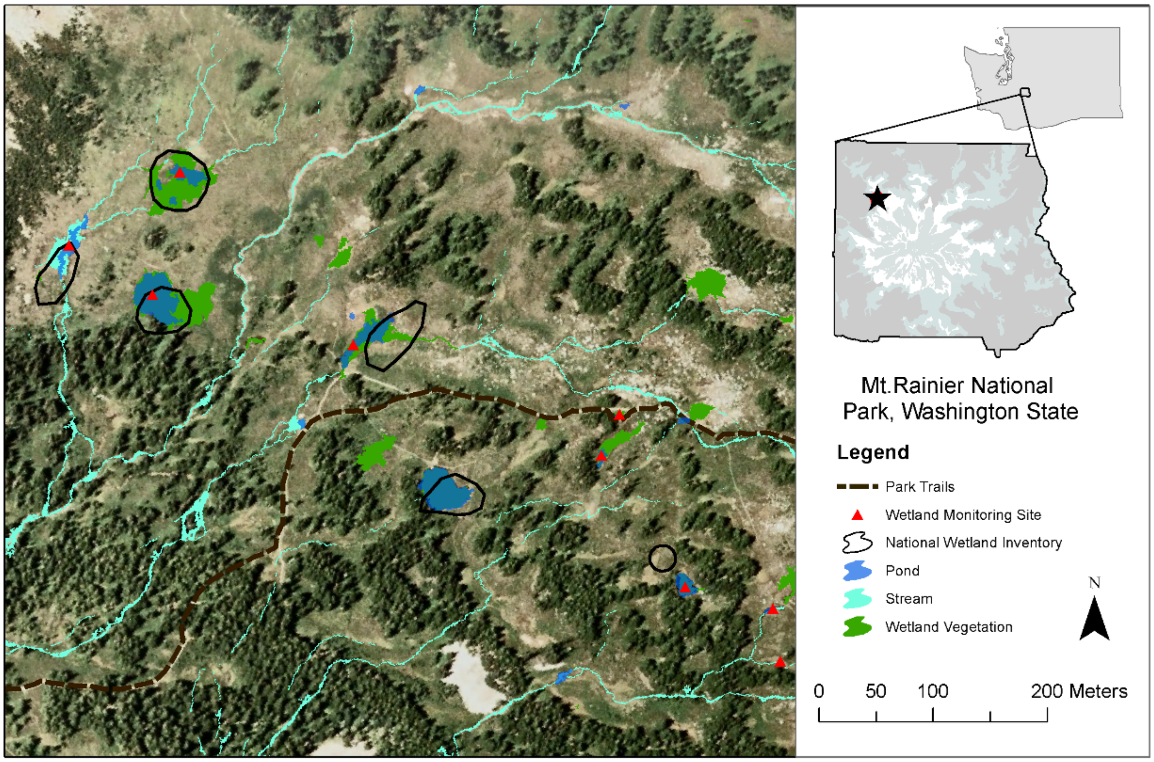


Figure 3.1.1: Example of classification output for Spray Park, Mt. Rainier National Park compared to the National Wetland Inventory.

Table 3.1.1: Comparison of wetland inventories to 31 groundtruthed wetland monitoring sites.

	Spray Park	Palisades	Mazama Ridge	Total	Accuracy
NWI	6	7	6	19	61.3%
OBIA using DEM	5	7	6	18	58.1%
OBIA using LiDAR	12	8	8	28	90.3%
Monitoring Sites	15	8	8	31	

monitoring sites, worse than the National Wetland Inventory. The DEM classification was unsuccessful because although the DEM had a resolution of 10 meters it was derived from 30 meter satellite data and could not pick up small elevational changes. Measurements of slope, therefore, were not useful in predicting wetlands. In addition, without the use of LiDAR intensity imagery, shadows from trees and topography could not be removed. We tested our algorithm on our other montane sites, Olympic National Park and North Cascades National Park, with similar results. Any attempts at adapting the DEM algorithm to better map wetlands in these two parks caused either high errors of commission (mapping shadows as wetlands) or errors of omission (failing to map wetlands). Therefore, we determined that we could not map wetlands in mountainous areas without additional data; either LiDAR, radar, or additional dates of high resolution imagery. (For this reason we use the NWI in the Synthesis results below.)

Figure 3.1.2: Example of high resolution aerial imagery compared to LiDAR intensity for Mazama Ridge, Mount Rainier National Park. Wetlands are circled in red. LiDAR intensity imagery helps remove the confusion between shadows and water.

Of these datasets LiDAR data is the most ideal for mapping wetland in mountainous areas as it is an active sensor with a high spatial resolution. Because LiDAR is an active sensor, and therefore does not passively measure reflected sunlight, it does not capture shadows caused by sunlight hitting trees and areas of steep topography. Infrared light, which was used for this LiDAR acquisition is highly absorbed by water and is useful in detecting waterbodies, such as ponded wetlands. Figure 3.1.2 shows the advantages of LiDAR intensity compared to high resolution aerial imagery in removing shadows and locating areas of water. However, theoretically multiple dates of imagery could also ameliorate the issue of shadows on the landscape as they tend to have a distinct spatiotemporal pattern different from wetlands. Because we were limited to only two dates of aerial imagery we could not test this idea.

Predicting Pond Drying Rate

Our approach using remotely sensed variables to predict slope of pond drawdown did not produce conclusive results. There was no single remotely sensed variable that could be used to predict pond rate of drying. This may be due to the low sample size (31) and/or the high variability of wetland types and hydrologic drivers of wetland hydrology. Although the variables had low R^2 values, the remote sensing variables calculated on both hierarchical levels, wetland complexes and ponds, showed significance to pond drying (Table 3.1.2). The relative area of deep water mapped using 2008 LiDAR intensity imagery to the total area of the wetland complex was the best predictor with a R^2 value of 0.39. The next best predictors were the relative area of deep water mapped using 2009 false color imagery and the maximum topographic wetness index calculated within a wetland complex. Other significant variables were TWI calculated within just the ponded area of a wetland, the relative area of a pond which is deep enough to fully absorb LiDAR, the mean TWI for a wetland complex, the minimum slope calculated within a pond, the mean topographic wetness index of a pond, and the relative area of deep water calculated using 2008 LiDAR intensity imagery.

Table 3.1.2 Remotely sensed variables predicting the slope of pond drawdown

Variable	Calculated on:	R2	P - value
Relative area deep water area in 2008	wetland complex	0.39	0.0002
Relative area of deep water in 2009	pond	0.38	0.0002
Maximum topographic wetness index (TWI) value	wetland complex	0.38	0.0003
Maximum topographic wetness index (TWI) value	pond	0.33	0.0008
Relative area deep water area in 2009	wetland complex	0.29	0.0018
Relative area LiDAR is fully absorbed	pond	0.26	0.0034
Mean topographic wetness index (TWI) value	wetland complex	0.26	0.0036
Minimum slope value	pond	0.22	0.0073
Mean topographic wetness index (TWI) value	pond	0.22	0.0085
Relative area deep water area in 2008	wetland complex	0.19	0.0136

Columbia Plateau Wetlands

Our method combining high resolution imagery with Landsat satellite imagery to reconstruct wetland hydrographs in the Columbia Plateau produced detailed hydrographs for 2,475 wetlands spanning a time period from 1984 – 2011. The individual hydrographs capture both long-term change and seasonal change to surface water of wetlands (Figure 3.1.3).

Comparisons of the SMA surface water estimates to the validation dataset show a Pearson's R value of 0.987 (p< 0.001) (Figure 3.1.4, left panel). Percent surface water estimates, as expected, had a lower correlation, with a Pearson's R value 0.845 (p< 0.001) (Figure 3.1.4, right panel). Although, still low, further examination of the residuals compared to the size of the wetlands shows a larger magnitude of error for smaller wetlands (Figure 3.1.5). However, even hydrographs for wetlands less than one Landsat pixel provide insight into long-term wetland hydrology (Figure 3.1.6).

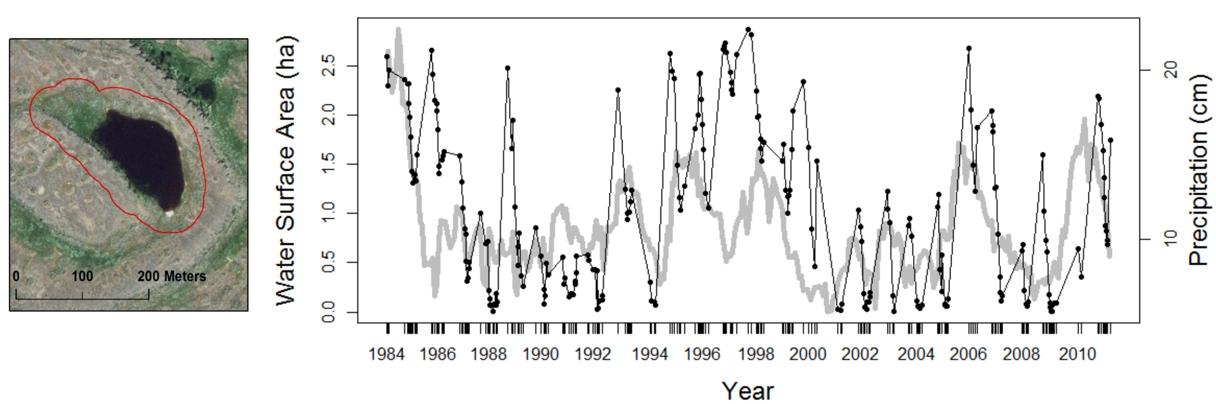


Figure 3.1.3: Example of a surface water hydrograph spanning from 1984 - 2011. This figure represents the hydrograph of the wetland on the left, which is 3.4 hectares in size. X-axis tick marks represent number of observations. Reconstructed hydrograph measures both inter- and intra- annual change. A moving average of annual precipitation calculated by month is shown in grey. The hydrograph of this wetland tracks changes in precipitation levels.

This dataset provides rich hydrological data spanning 26 years that can be mined to classify wetland habitat types, identify abnormal changes to wetland hydrology, monitor surface water availability throughout the landscape and serve as a source for wetland hydrologic research at different temporal scales. Figure 3.1.7 provides an example of mining the hydrological data for wetland classification purposes. Although there are various ways to classify wetlands from the hydrological dataset, we chose to classify wetlands at two temporal scales. First, we used the entire dataset to categorize wetlands
based on the % years that a wetland dried. Secondly, we extracted the hydrographs for a typical climate year (2011) and classified wetlands based on their drying rate and drying day. The hydrographs taken from 2011 mimic the classes we used for montane sites. The benefit of using the entire timespan to classify wetlands is that we capture more of the inter-annual variability of

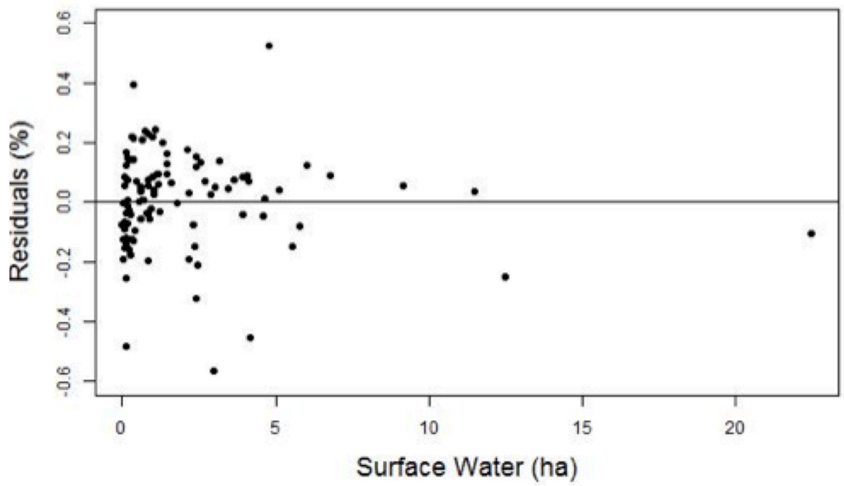


Figure 3.1.5: Residuals of relationship between percent actual surface area to percent predicted surface area. Surface water extent as measured by the validation dataset is plotted on the x-axis.

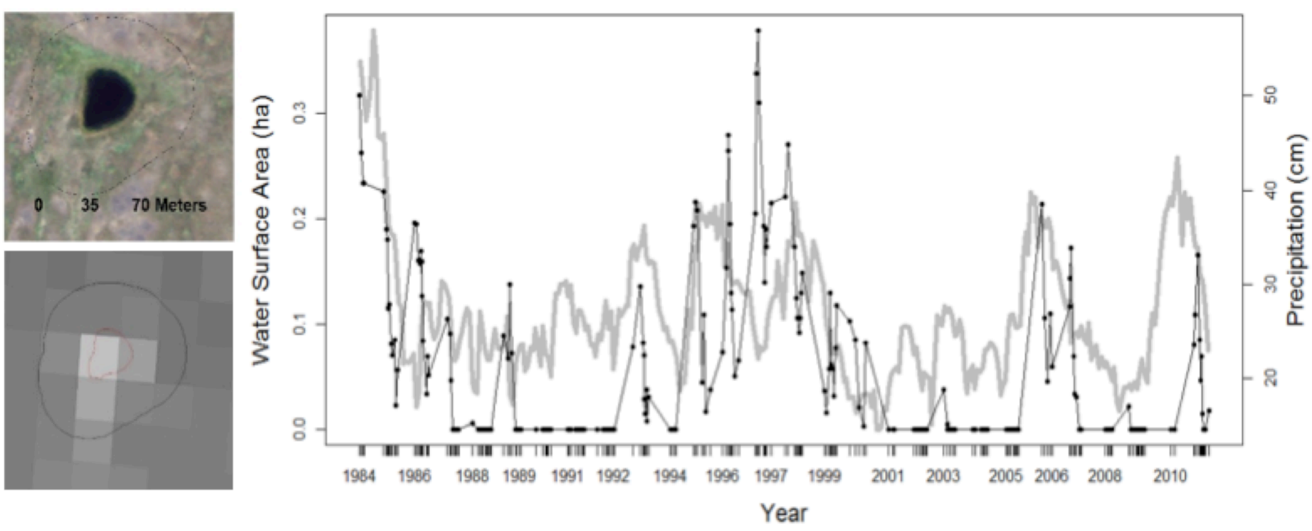


Figure 3.1.6: Example of a hydrograph for a small wetland. The surface area of the validation dataset (derived from 2011 aerial image) estimated the surface area to be only 800 square meters in size (less than one Landsat pixel), however, this hydrograph still tracks precipitation patterns and provides useful information of the hydrology of this wetland. A moving average of annual precipitation calculated by month is shown in grey.

each wetland. The benefit of classifying wetlands using a recent typical climate year is that some wetlands may have changed classes over the 26-year timespan (e.g. permanently flooded to intermediate) due to human-induced change. Because we ran the VIC analysis on all wetlands we did not need to classify wetlands *a priori* as we did for the montane sites. This allowed us to explore the spatiotemporal patterns with a continuous variable rather than discrete categories, since hydrologic drivers and related ecological thresholds may differ between the Columbia Plateau and montane wetlands.

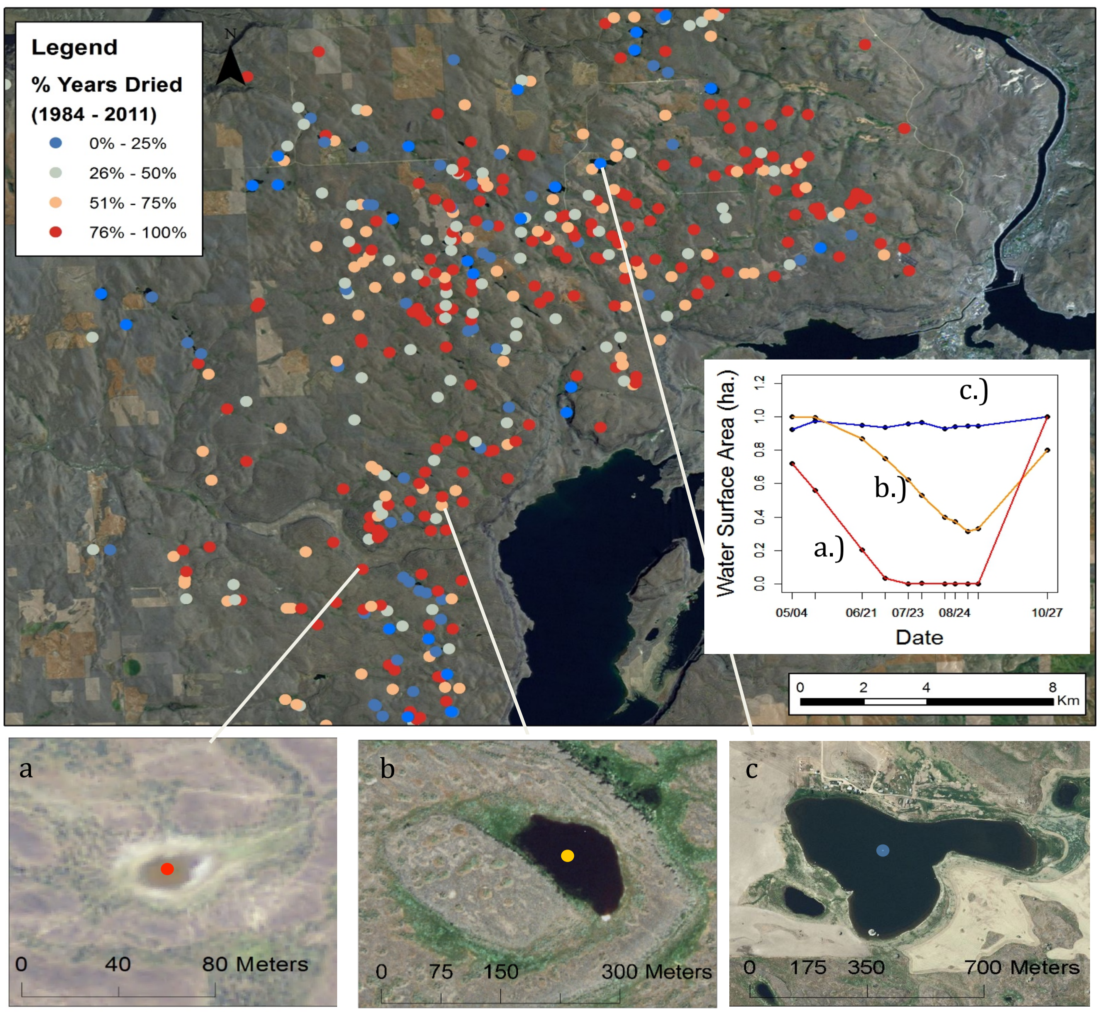


Figure 3.1.7: Example of a hydrograph for three different wetland types for the year 2011; ephemeral wetland (a), intermediate wetland (b), and a permanent wetland (c). The map shows the spatial variability of wetland types in northeast Douglas County based on the number of years the wetland fell below 20% water surface area between 1984 and 2011.

We also found evidence of wetlands undergoing abnormal change. For example, Figure 3.1.8 shows three examples of wetlands with abnormal hydrographs: (top) provides the hydrograph for a wetland that is drying out over time and is now is only 50% of the total surface area it was in the mid-1980s. Figure 3.1.8 (middle) shows a hydrograph of a wetland that is repeatedly plowed over for farming. Figure 3.1.8 (bottom) shows a hydrograph of a wetland that was created through hydrologic engineering.

The results derived from the remote sensing methods described here are integrated with the climate change projections into a geodatabase which includes hyperlinks to reconstructed hydrographs as well as predicted wetland hydrographs. This interactive map allows researchers, policymakers, and managers to see patterns of change at different spatial and temporal scales, both across the entire Columbia Plateau landscape and at the local scale (Figure 3.1.9). Our geodatabase will be provided to land managers in each of the focal regions in the Columbia Plateau and is available upon request.

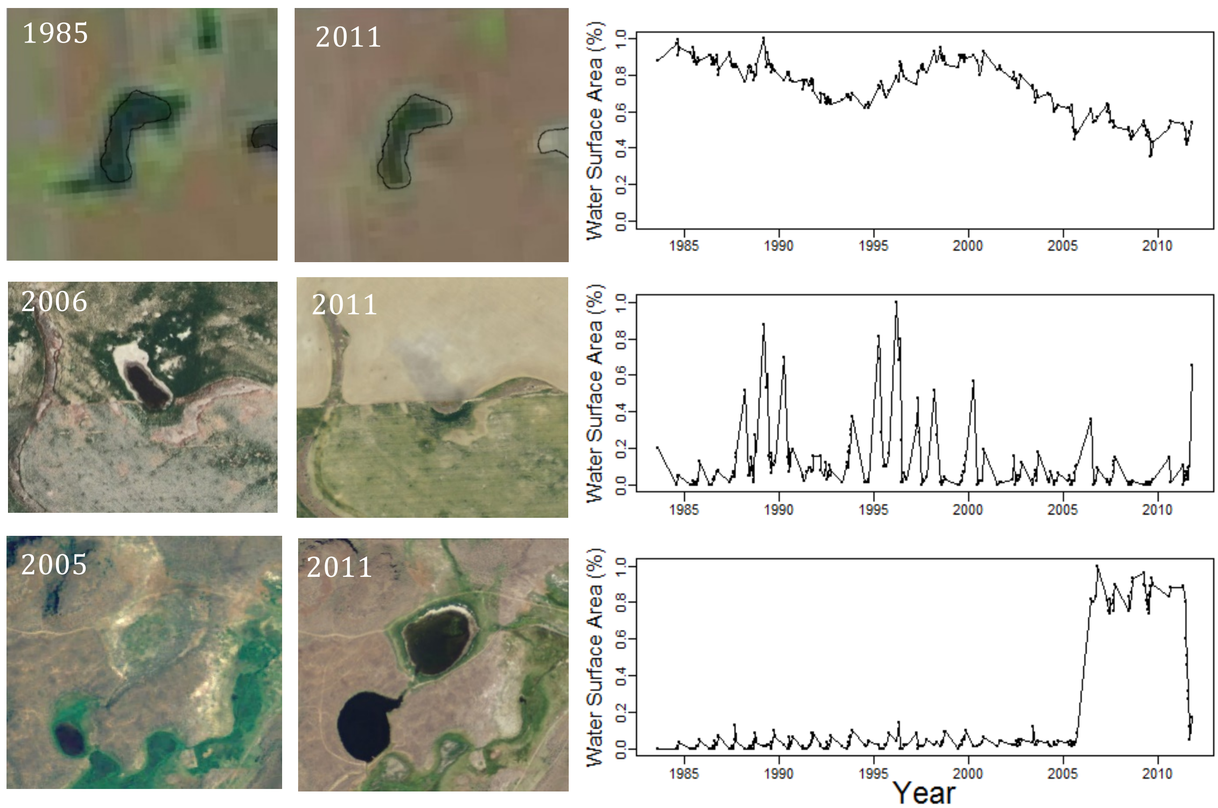


Figure 3.1.8: Example of hydrographs for three wetlands undergoing abnormal change; shrinking wetland (top), plowed wetland (middle), and created wetland (bottom).

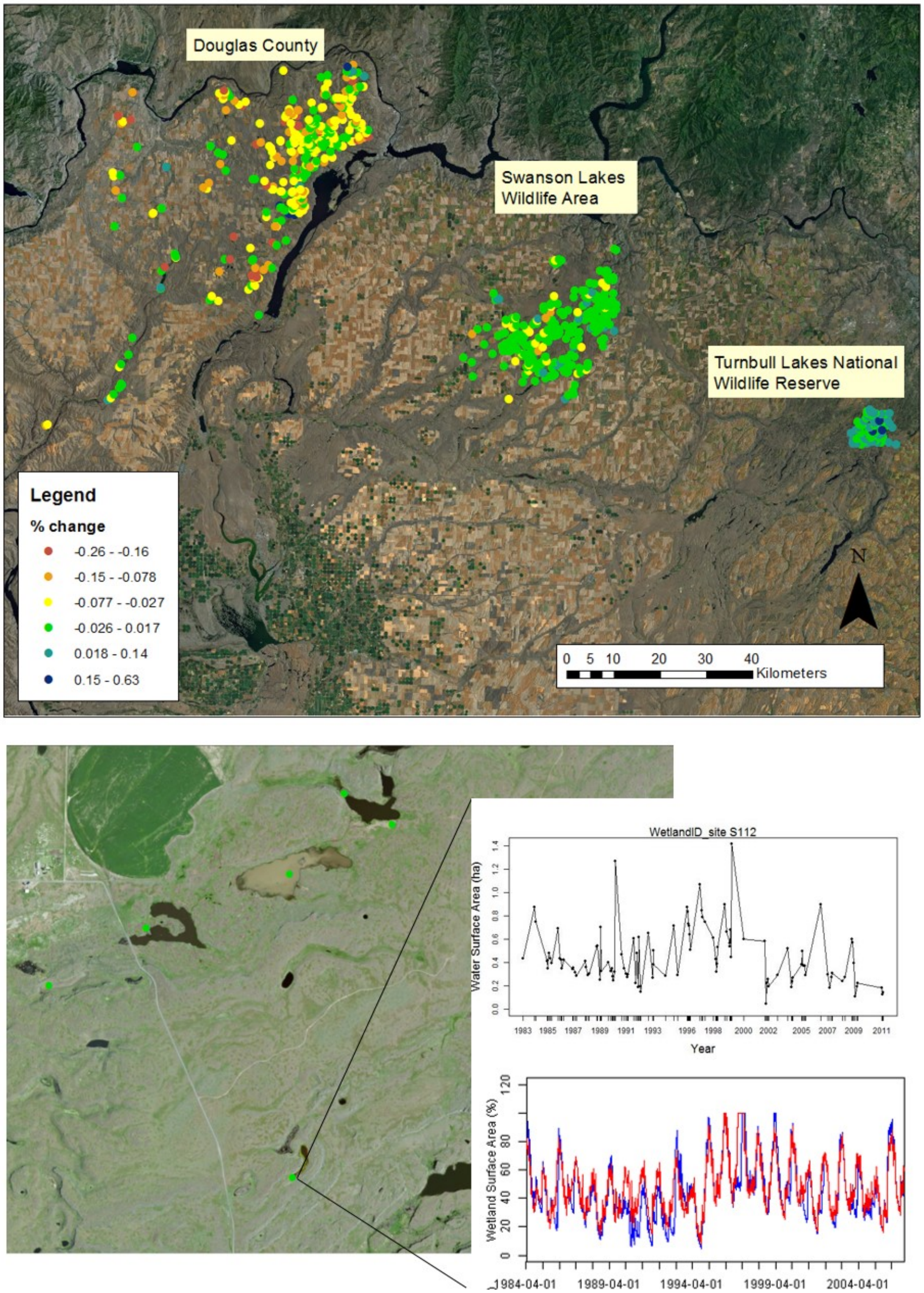


Figure 3.1.9: Example of interactive wetland map created for the Columbia Plateau using a geodatabase created for this project. This map provides users with an interactive approach to detecting changes to wetlands at multiple temporal and spatial scales. The top image is an example of changes in wetland hydrology between 1984 – 2011 at the landscape scale. The bottom image shows historic and future hydrographs for an individual wetland.

3.2. Monitoring of Focal Field Sites

Montane Wetlands

Hydrologic monitoring results are integrated into Section 3.3 below. Amphibian survey results are integrated into Section 3.4 below. Appendix B lists all monitored and surveyed sites.

Puget Lowlands Wetlands

Results are integrated into Section 3.3 below.

Columbia Plateau Wetlands

IButton dataloggers were placed in Fall 2012 and Spring 2013, and all were retrieved in Fall 2013. Unfortunately, cloud-free satellite imagery was not available for the same time period, and iButtons in some cases sank into thick mud that obscured their signal, so we could not use the iButtons as a strong source of validation.

3.3. Climate-Hydrologic Modeling

Montane Wetlands

Historical reconstruction of wetland dynamics

The soil moistures in the middle and bottom soil layers were better correlated with observed wetland water levels than other water balance variables (Fig. 3.3.1). The best predictor differed among years and regions. Soil moisture in the middle soil layer was the best predictor for ephemeral, intermediate, and perennial wetlands based on observed data in 1992 for Mount

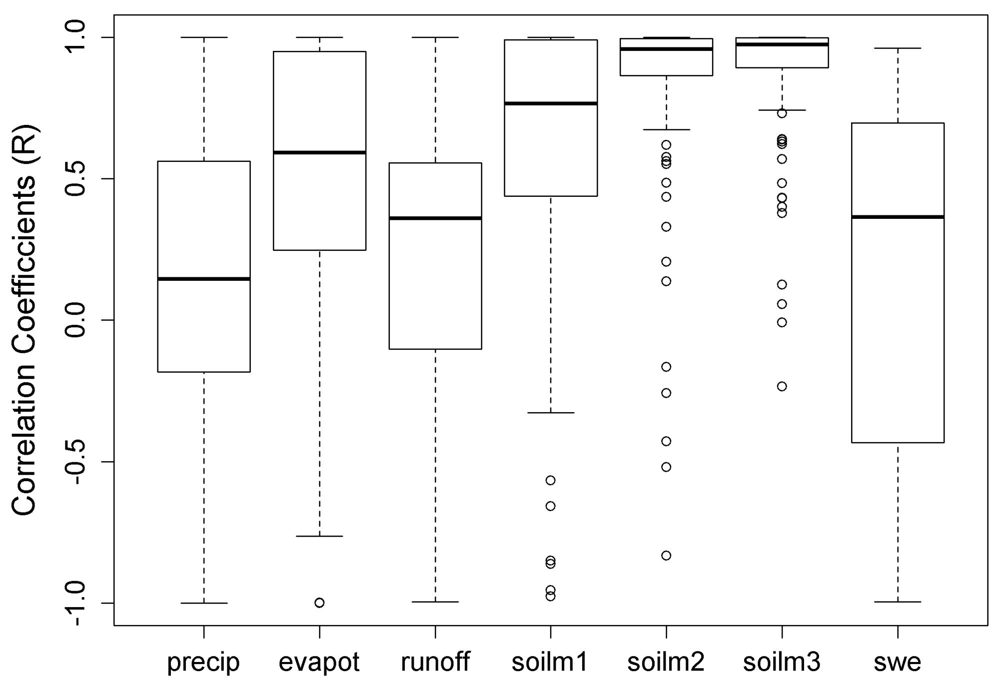


Figure 3.3.1. Correlation coefficients between observed water level and simulated water balance variables such as precipitation (precip), evapotranspiration (evapot), runoff, soil moistures in the top (soilm1), middle (soilm2), and bottom (soilm3) layers, and snow water equivalent (swe).

Rainier National Park and 2000 for Olympic National Park. However the strength of correlations differed substantially between the 1992 Mount Rainier and 2000 Olympics datasets, with fairly strong correlations between wetland water levels and middle layer soil moisture in Mount Rainier and far weaker correlations and poor overall model performance in the Olympic sites in 2000. Overall, though, soil moisture in the bottom soil layer was the best predictor for all wetlands except the 1992 Mount Rainier and 2000 Olympics datasets, with fairly robust correlations between simulated and empirical data. After choosing the best single predictor for each wetland, we developed a regression model for each individual wetland.

The R^2 values showed that the regression models match empirical observations reasonably well, with a mean R^2 for all for wetland types above 0.8, though a few wetlands (6 out of 125; 4.8%) had an R^2 value below 0.6. Overall, ephemeral and intermediate wetlands showed the best model fits, while perennial ponds had the weakest fit among wetland types (Fig. 3.3.2). The observed timing and pattern of seasonal drawdown generally were captured well by simulations for montane wetlands across the majority of our different sites ($0.82 < R^2 < 0.97$) (Figs. 3.3.3-4). Figure 8 illustrates representative wetlands for each pond type from Mount Rainier (left column) and Olympic National Parks (right column), selected from sites with the most observed data. Exceptions to the overall good model performance were the minimum water level for the year 2006 for Deschutes National Forest, Oregon (Fig. 3.3.4a) and the timing of drawdown for the year 2003 in Trinity Alps Wilderness, California (Fig. 3.3.4c). For the Deschutes National Forest, the observed minimum water level for year 2006 was 13% of full capacity but the simulation minimum was 22-34%. For the Trinity Alps Wilderness site, the wetland started drawdown about one month later in 2003 compared to the other years but the simulation was not able to reproduce this timing.

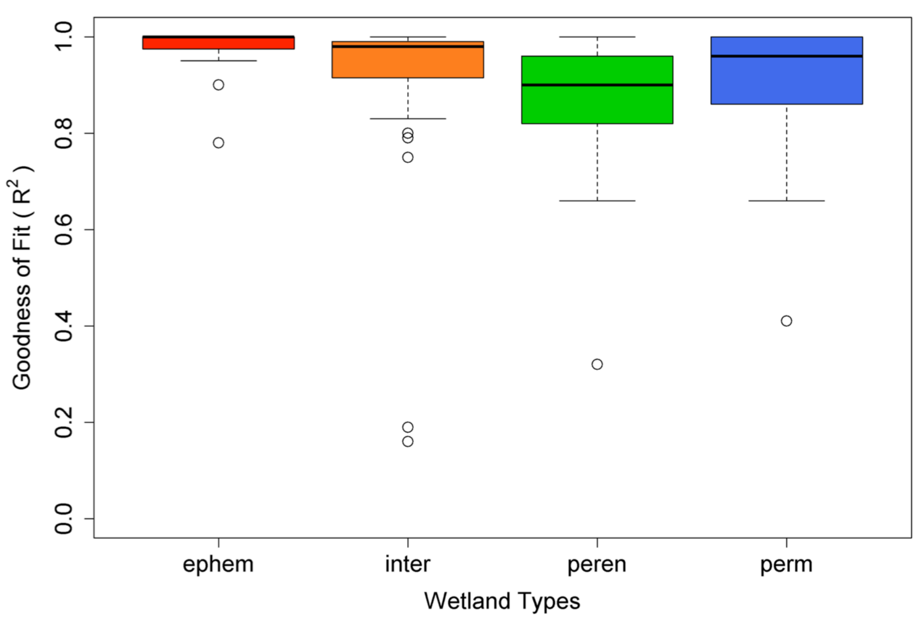


Figure 3.3.2. Boxplot of goodness of fit (R^2) between observed and simulated data for each wetland type.

For sites where multiple years of data existed, we found considerable uncertainty and variation in model performance (Figs. 3.3.4-6). For example, different regression models for the Trinity Alps (CA) site, constructed using different years of data, showed an average difference of 47 days between the earliest and latest prediction of minimum water levels in summer (Fig. 3.3.4c). While the regression model for Mount Rainier National Park developed based on 1992 data ($0.83 < R^2 < 0.99$) also captured the observed drawdown at the same wetlands in 2012 (0.88

< R^2 < 0.995) (Fig. 3.3.5), model performance across different years was poor for Olympic National Park. For Olympic National Park, the regression model based on 2000 observations missed the timing of drawdown and/or minimum water levels observed in 2012 (Fig. 3.3.6). We therefore might expect comparable levels of uncertainty in the performance of the single-year regression fits for the broader suite of wetlands at Mount Rainier, Olympic and North Cascades National Parks.

Investigating the threshold for wetland drying we found that, on average across regions, wetland drying occurred when soil moisture was at roughly 100% field capacity, though there was considerable variation among sites (Fig. 3.3.7). Therefore to have a single metric for landscape-scale analysis, we use 100% field capacity as a mean threshold of drying and proxy for intermediate wetland drying for each VIC grid cell. These values help quantify systematic changes in wetland response over large areas, but may not represent the details of individual wetland responses very well.

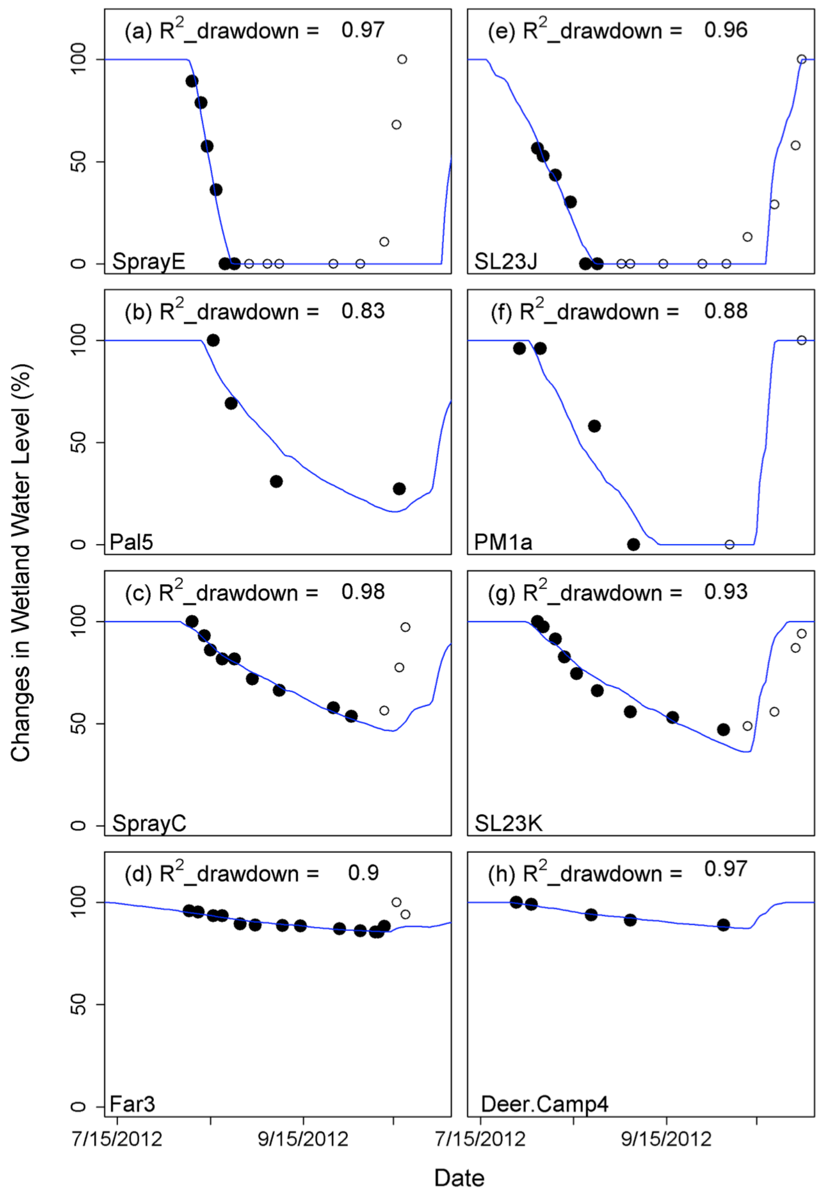


Figure 3.3.3. Four representative wetlands in Mt. Rainier National Park, WA (a-d) and in Olympic National Park, WA (e-h) for ephemeral hydroperiod (a,e), intermediate hydroperiod(b,f), perennial (c,g) and permanent wetland (d,h). Solid circles show observed data that are used for developing regression model and calculating R^2 values and open circles are remaining observed data. Blue lines are simulated wetland levels.

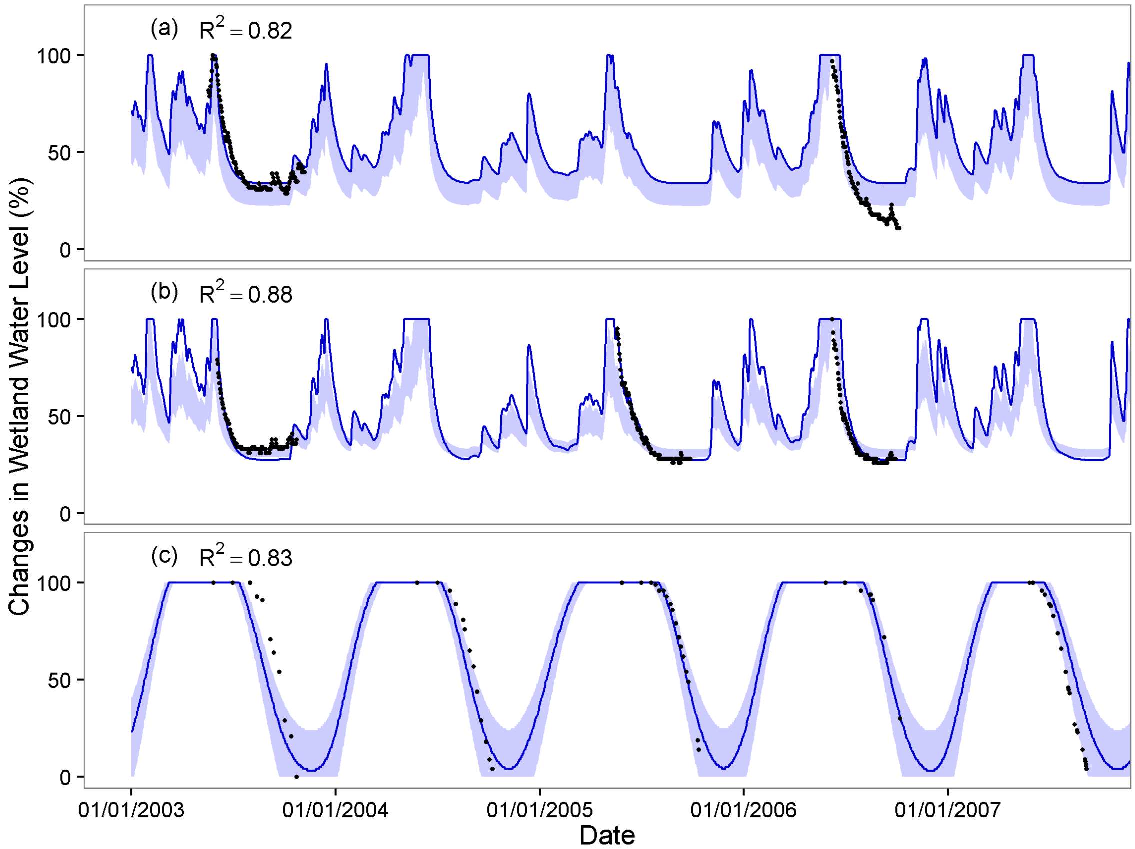


Figure 3.3.4. Observed wetland water levels compared with simulation using the regression models for a) Deschutes National Forest, OR, b) Willamette National Forest, OR, and c) Trinity Alps Wilderness, CA. Dark blue lines are produced by the regression equation deriving from the best fit from all available years. Blue bands show the range of uncertainty associated with alternate regression parameters deriving from other years of data.

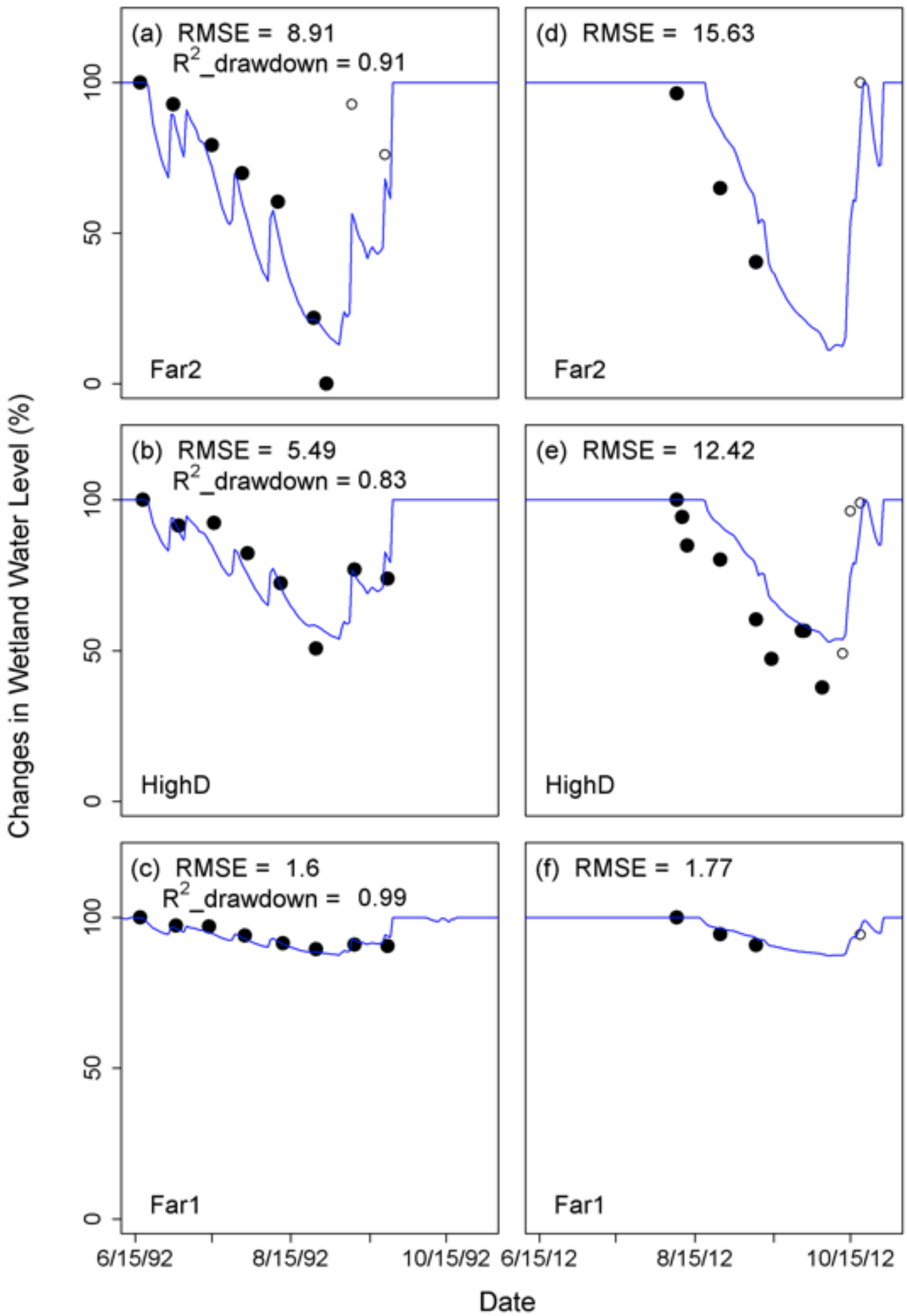


Figure 3.3.5. Observed wetland water level for year 1992 (a-c) and for year 2012 (d-f) for ponds at Mount Rainier National Park compared with the simulated wetland water levels using the regression model that were developed based on 1992 observation. Solid circles show observed data that are used for developing regression model and/or for calculating R^2 values and open circles are the other observed data. RMSE is the root mean squared error, which allows comparison of model fit for the two datasets.

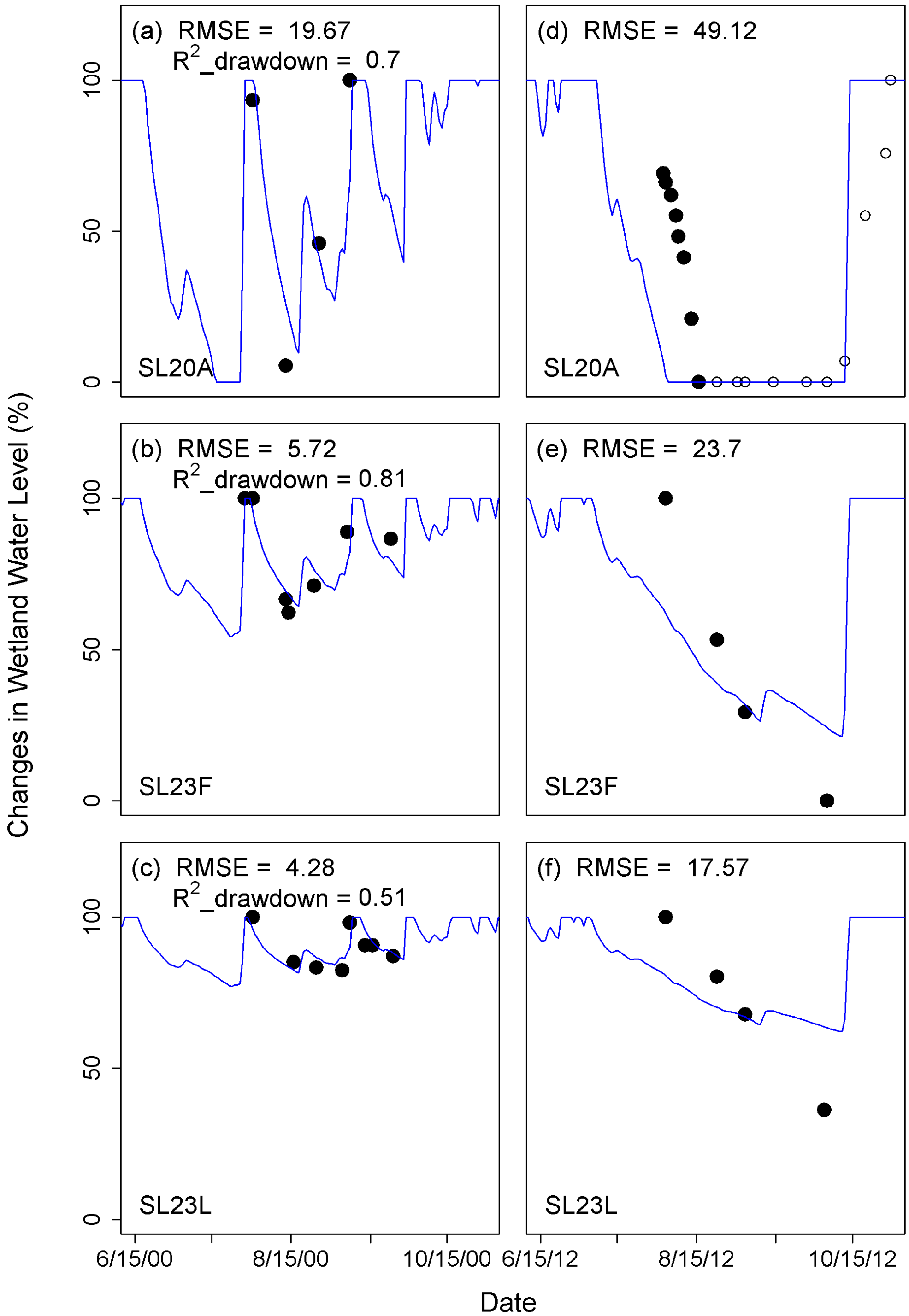


Figure 3.3.6. Observed wetland water level for year 2000 (a-c) and for year 2012 (d-f) for Olympic National Park compared with the simulated wetland water levels using the regression models that were developed based on 2000 observation. Solid circles show observed data that are used for developing regression model and/or for calculating R^2 values and open circles are the other observed data. RMSE is the root mean squared error.

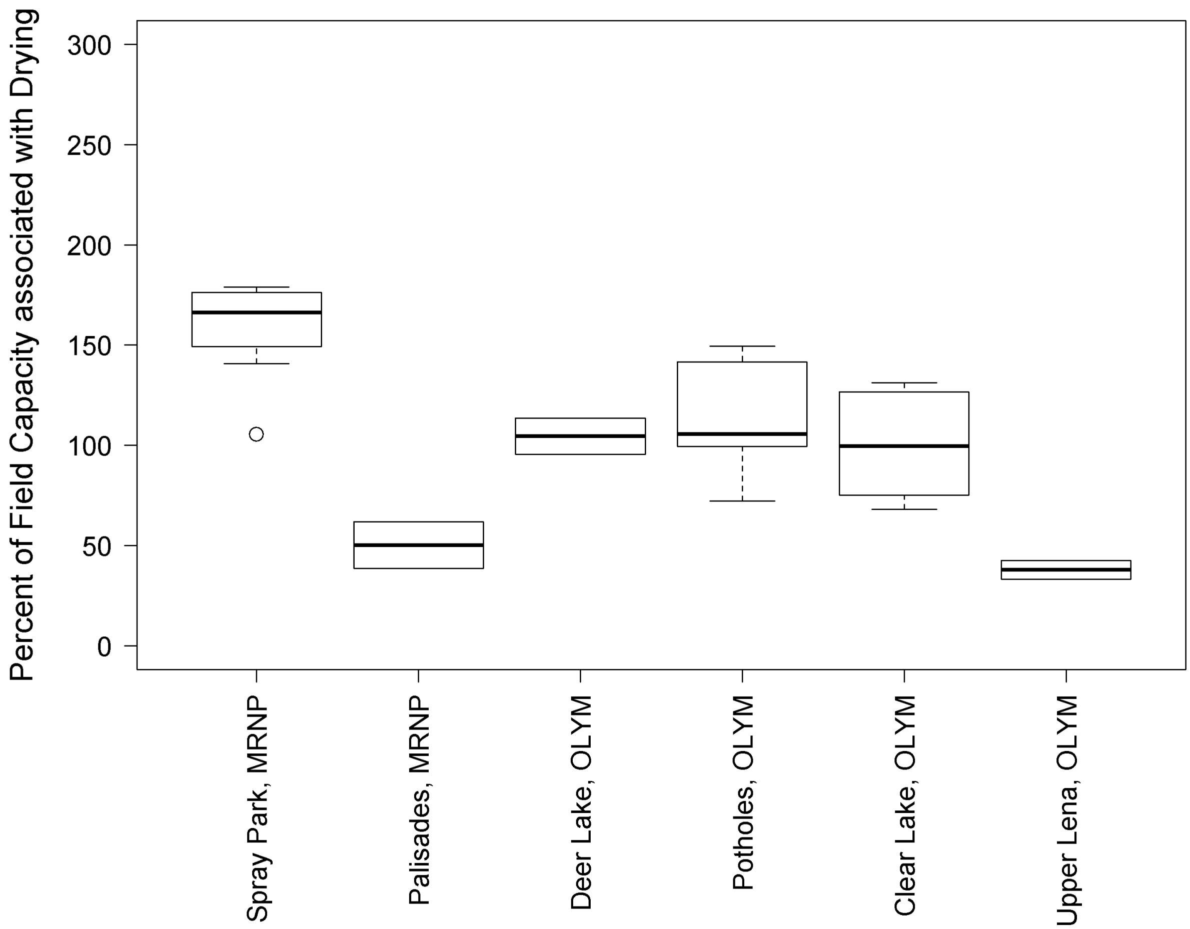


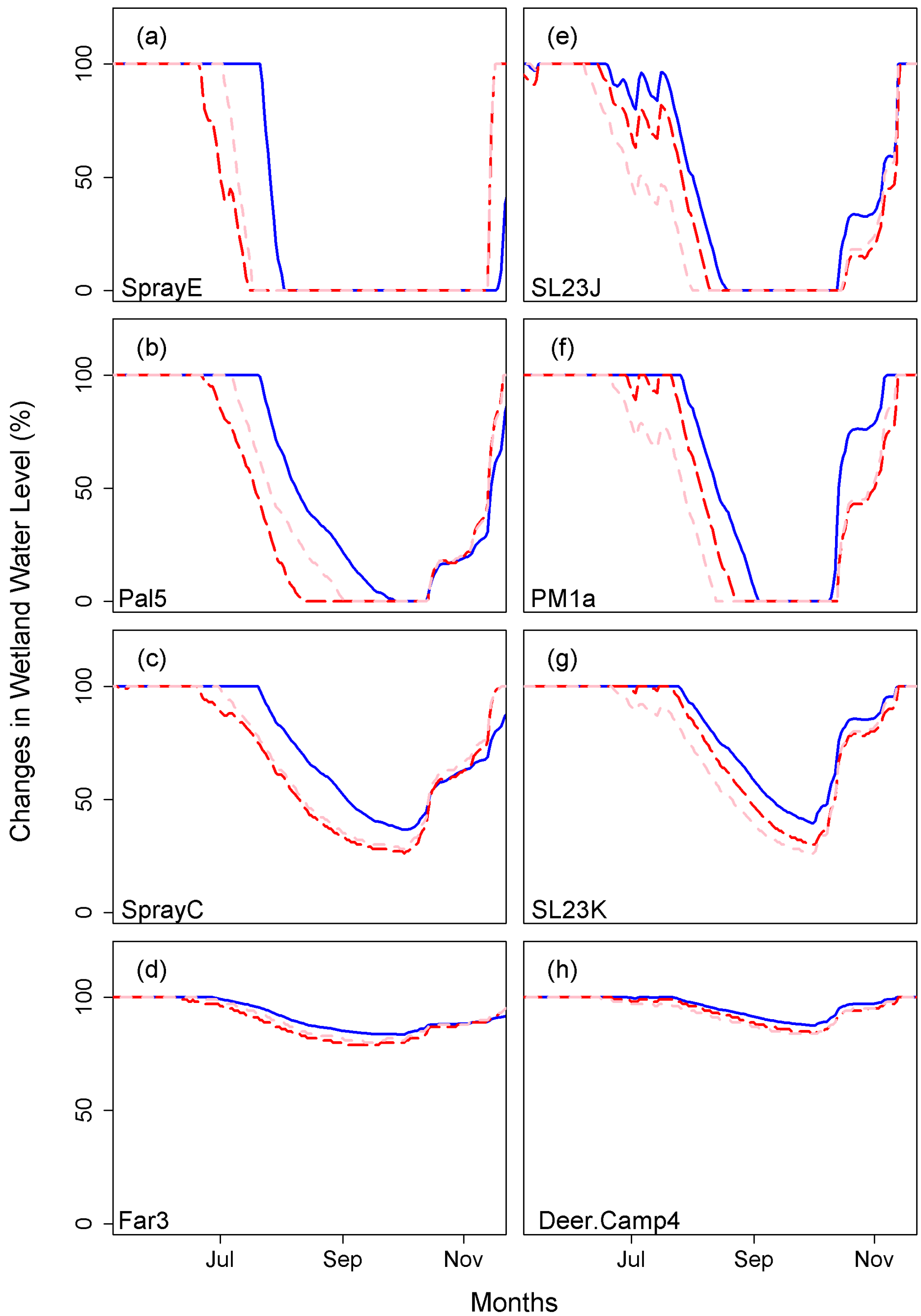
Figure 3.3.7. Relationship between percentage field capacity and wetland drying for intermediate wetlands across study regions. Spray Park and Palisades are in Mount Rainier National Park. (There were no intermediate wetlands by our definition in Mazama Ridge.) Deer Lake, Potholes, Clear Lake, and Upper Lena are regions of Olympic National Park.

Future climate projections of wetland dynamics

We found consistent projected effects of climate change on all classes of wetlands, including earlier drawdown, a more rapid recession rate in summer, and reduced minimum water levels (Figs. 3.3.8-9). Overall, water levels in ephemeral or intermediate wetlands are most sensitive to climate change (Fig. 3.3.8a-b and e-f). In ephemeral or intermediate wetlands, the effects of earlier drawdown, more rapid summer recession rate, and reduced minimum water levels result in a longer dry season in summer (Fig. 3.3.8a-b and e-f, and Fig. 3.3.10c). Results for perennial and permanent wetlands also showed earlier drawdown and/or reduced water levels in future climates (Fig. 3.3.8c-d and g-h and Fig. 3.3.9a-b). Our projections also revealed variations in the magnitude of changes that were dependent on wetland type and location.

These climate-induced shifts in hydrologic behavior across all types of montane wetlands in our study support the hypothesis that climate change will force transitions among wetland types (Fig. 3.3.11). By the 2080s, 58% of intermediate wetlands are projected to become ephemeral wetlands (17/31 sites), whereas 22% of perennial wetlands are projected to become intermediate wetlands (7/32 sites) and 3% to become ephemeral wetlands (1/32 sites) (Fig. 3.3.11b). Thirty-two percent of permanent wetlands are projected to become perennial (12/38 sites) (Fig. 3.3.11b).

Figure 3.3.8. Projected wetland response to climate change for sites in Mt. Rainier National Park, WA (a-d) and in Olympic National Park, WA (e-h) for ephemeral hydroperiod (a,e), intermediate hydroperiod (b,f), perennial (c,g) and permanent wetlands (d,h). Blue solid lines are wetland hydrographs for year 1998 and pink and read dashed lines show wetland hydrographs of year 1998 with climate change perturbation for the 2040s and 2080s, respectively.



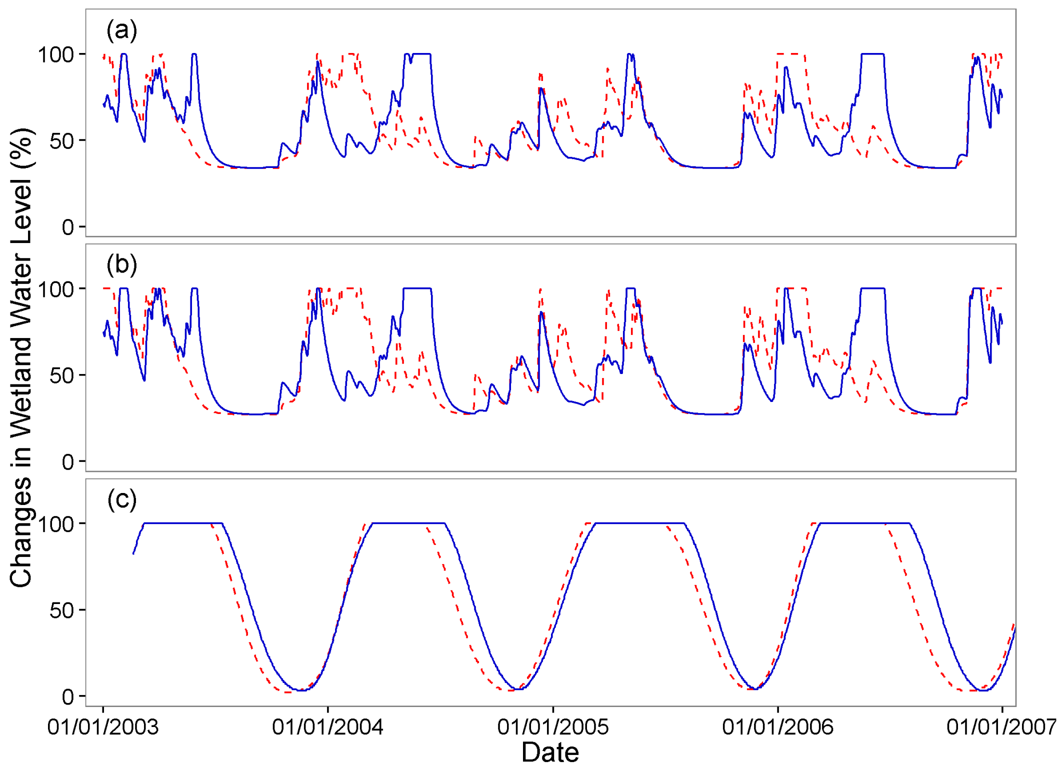
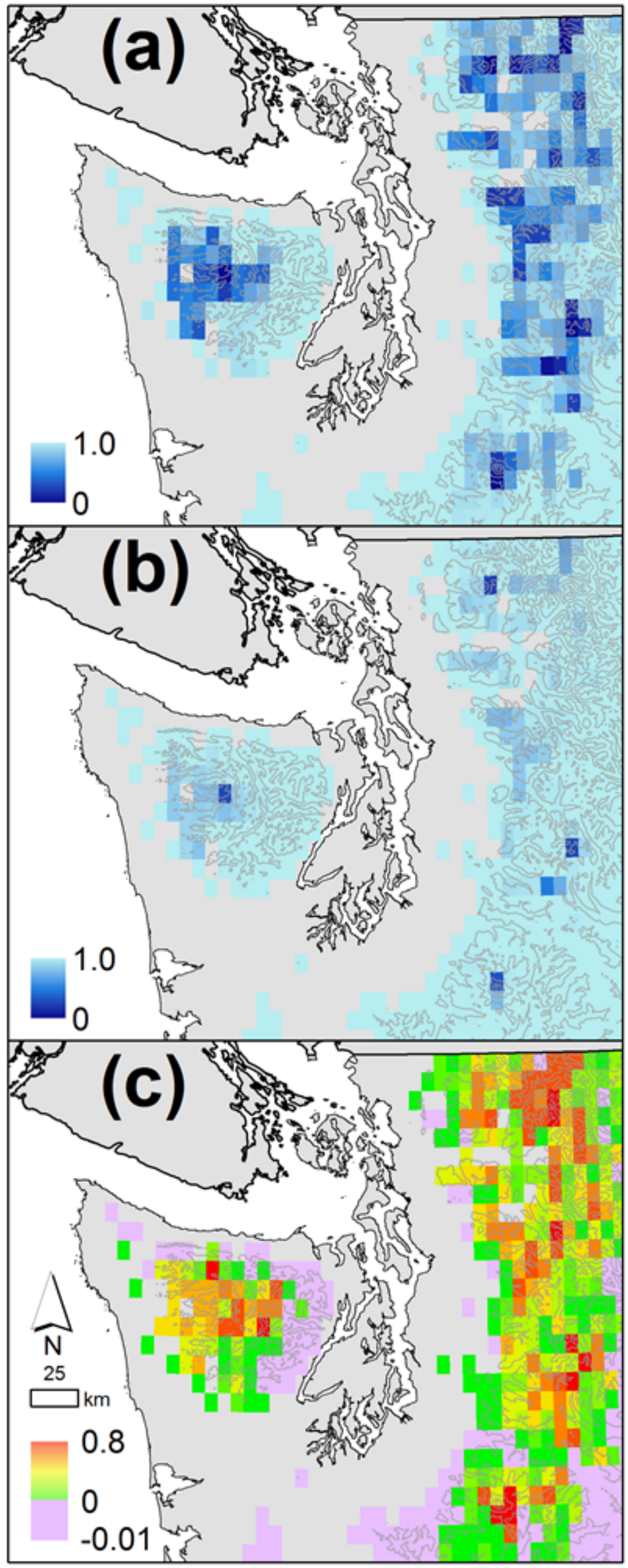


Figure 3.3.9. Projected wetland response to climate change for a) Deschutes National Forest, OR, b) Willamette National Forest, OR, and c) Trinity Alps Wilderness, CA. Blue solid lines are wetland hydrographs for years 2003-2004 and red dashed lines show wetland hydrographs of years 2003-2004 with climate change perturbation for the 2080s.

Figure 3.3.10. Map of the difference between historical probability of drying and that of the 2080s for intermediate wetlands in the mountains of Western Washington state. Projections for the 2080s are the average value for all ten GCM A1B scenarios. Colored grid cells are above 250m elevation, the region in which our projections are most relevant. Topographic contour intervals are 750m.



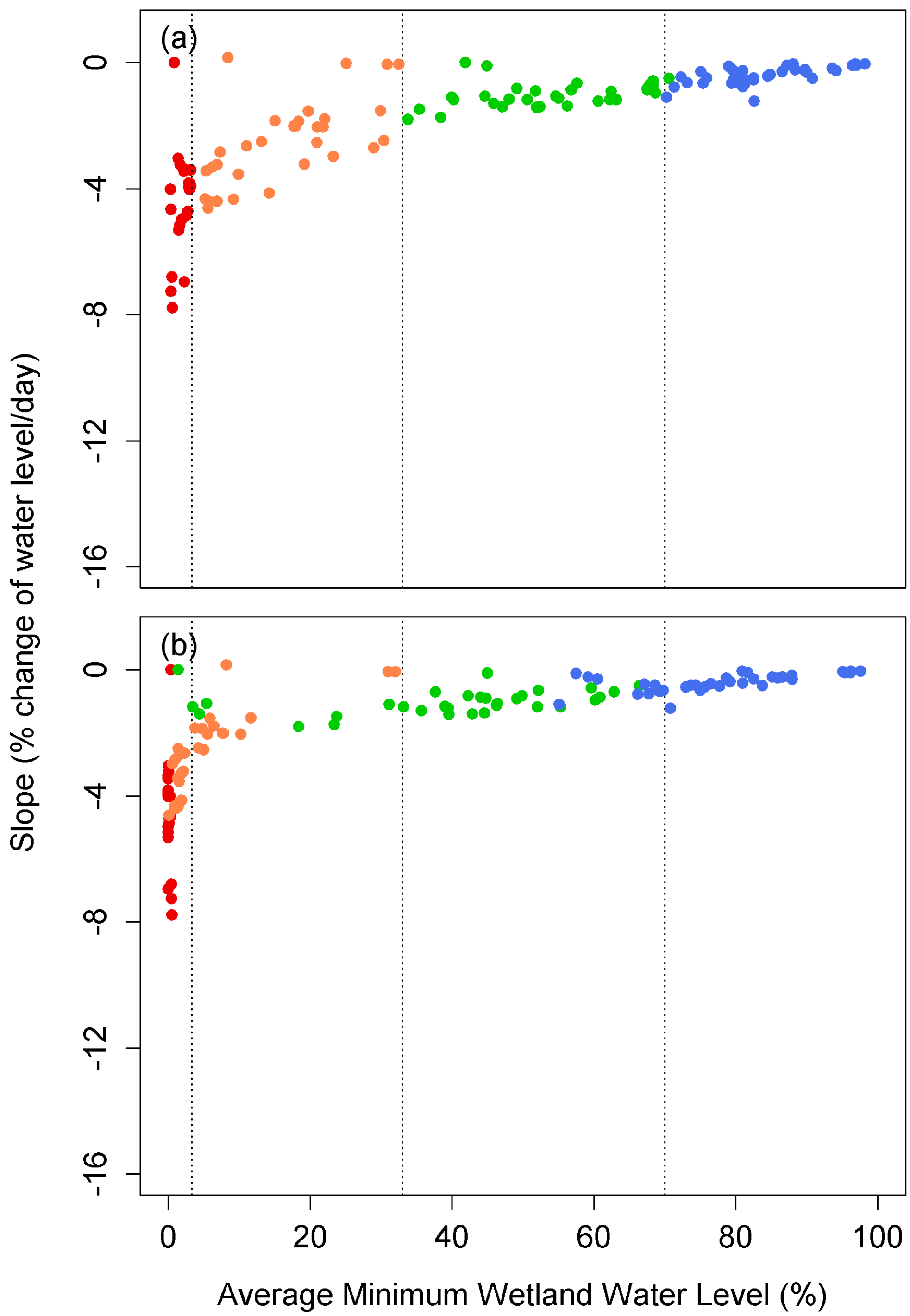


Figure 3.3.11. Scatterplots showing the slope of wetland drying versus the average of annual minimum a) for historical runs and b) for the 2080s. Reds are ephemeral hydroperiod wetlands, oranges are intermediate hydroperiod wetland, greens are perennial wetlands and blues are permanent wetlands.

Considered at the landscape scale, the projected effects of climate change on future probabilities of drying of intermediate wetlands in mountainous areas of Washington vary geographically but increase overall in higher elevation regions (Fig.3.3.10). Lowland areas are typically below the soil moisture threshold every year, and the probability of drying (by this measure) does not change in these areas, thus our model is not appropriate for assessment of lower elevation regions (grey areas on the maps). Similarly, many mid-low elevation regions show little change or even a small shift towards becoming wetter (light green and purple regions on maps). At higher elevations, both along the crest of the Washington Cascades and in the Olympic Mountains, the probability of drying for intermediate wetlands changes substantially. Under the 20th century climate, many cells had a probability of drying of 0.5 or lower for intermediate wetlands. By the 2080s, the projected probability of drying is greater than 0.8 for all but a few model cells, The largest changes in probability of drying were simulated for cells that historically represented the wettest regions in the model domain.

Water temperature modeling

The regression models reasonably captured historical water temperature variation, especially for ephemeral and perennial ponds (R^2 values generally >0.6) (Figures 3.3.12-14). While multiple sites dried, only one pond was classified as intermediate following our VIC analyses, hence the single data point in this category. All sites show an increase in average annual maximum temperature by the 2080s (roughly +2˚C average increase across sites) but with geographic variation in the amount of projected future change (Table 3.3.1, Figure 3.3.2). Our sample size is too small to robustly characterize spatial relationships in the data, though there are interesting

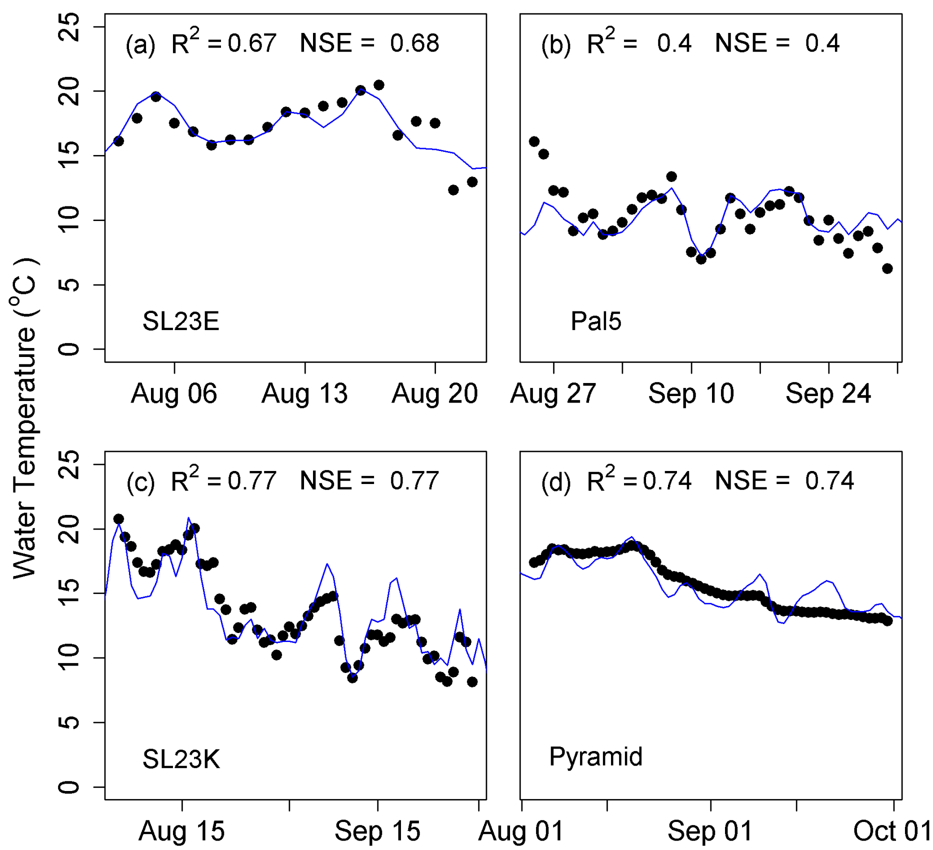


Figure 3.3.12. Four representative wetlands for ephemeral hydroperiod (a), intermediate hydroperiod (b), perennial (c) and permanent wetlands (d). Solid circles show observed water temperatures (°C) that were used for developing the regression model and calculating R^2 and NSE values. Blue lines are simulated wetland water temperature (°C).

hints of possible patterns that generate hypotheses to explore further. For example, these preliminary data suggest that the intensity of impacts on water temperature may be related to elevation and aspect. For example, note variation in intensity in the three study regions in Mount Rainier National Park, or two focal regions in Olympic National Park (Figure 3.3.15). Also, in our small sample of permanent wetlands, the mid-elevation wetland (~1500m) was most sensitive to climate change in comparison with both higher and lower elevation permanent wetlands (Figure 3.3.16b). We also found a hint of an elevational gradient in model fit (Figure 3.3.16a).

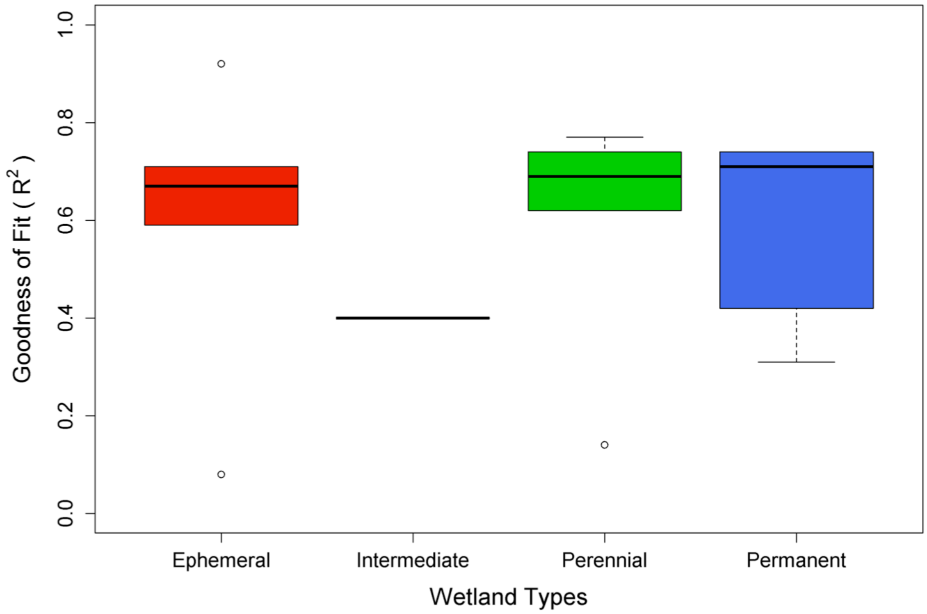


Figure 3.3.13. Boxplot of goodness of fit (R^2) between observed and simulated water temperature data for each wetland type.

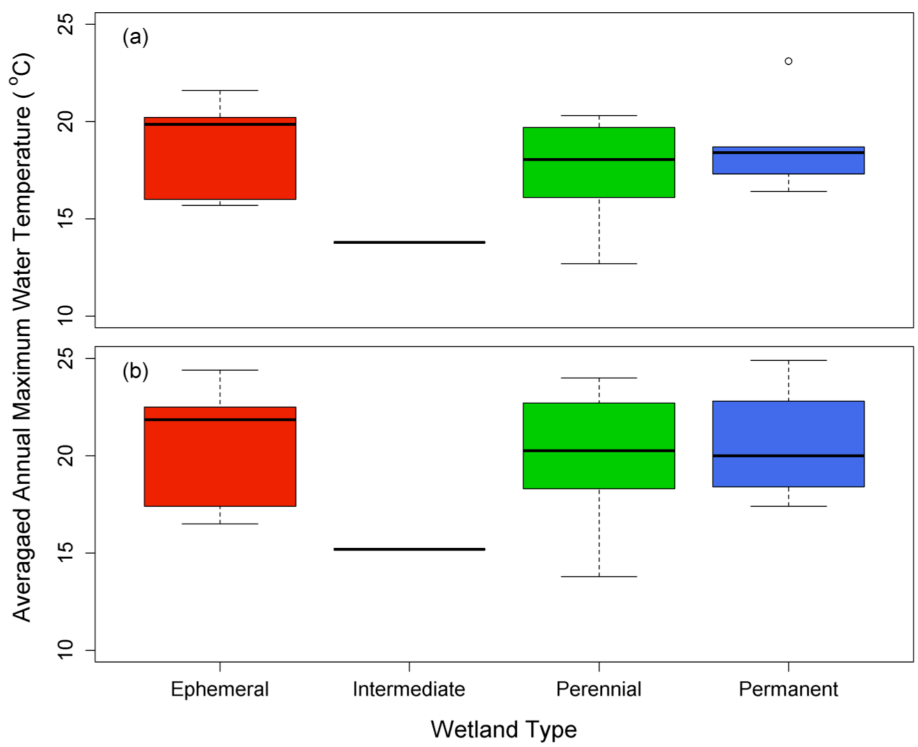


Figure 3.3.14. Boxplot of simulated annual maximum water temperature for each pond type for a) historical run and b) the 2080s.

Table 3.3.1 List of the 18 wetlands monitored with iButtons during summer of 2012 (August to October) used in the temperature analysis, and their simulated average annual maximum water temperature for the historical period and the 2080s. Under site locations, MRNP is Mount Rainier National Park, NCNP is North Cascades National Park, and OLYM is Olympic National Park.

Site Location	Type	Name	Averaged Annual Max Temp	
			Historical	2080s
Clear Lake, OLYM, WA	Ephemeral	SL20A	19.9	21.4
Clear Lake, OLYM, WA	Ephemeral	SL23E	19.8	22.3
Clear Lake, OLYM, WA	Ephemeral	SL23J	20.2	22.5
Clear Lake, OLYM, WA	Perennial	SL23I	19.7	22.7
Clear Lake, OLYM, WA	Perennial	SL23K	20.3	24.0
Clear Lake, OLYM, WA	Perennial	SL26B	16.1	19.1
Deer Lake, OLYM, WA	Ephemeral	Deer Camp5	16.0	17.4
Deer Lake, OLYM, WA	Perennial	Deer Meadow9	12.7	13.8
Palisades, MRNP, WA	Ephemeral	Pal3	15.7	16.5
Palisades, MRNP, WA	Intermediate	Pal5	13.8	15.2
Palisades, MRNP, WA	Permanent	Pal10	17.3	18.4
Palisades, MRNP, WA	Permanent	Pal8	16.4	17.4
Spray Park, MRNP, WA	Ephemeral	SprayE	21.6	24.4
Spray Park, MRNP, WA	Perennial	SprayC	19.3	21.4
Spray Park, MRNP, WA	Perennial	SprayP	16.8	18.3
Mazama Ridge, MRNP, WA	Permanent	Far 3	18.7	22.8
NCNP, WA	Permanent	Pyramid	18.4	20.0
NCNP, WA	Permanent	Thunder	23.1	24.9

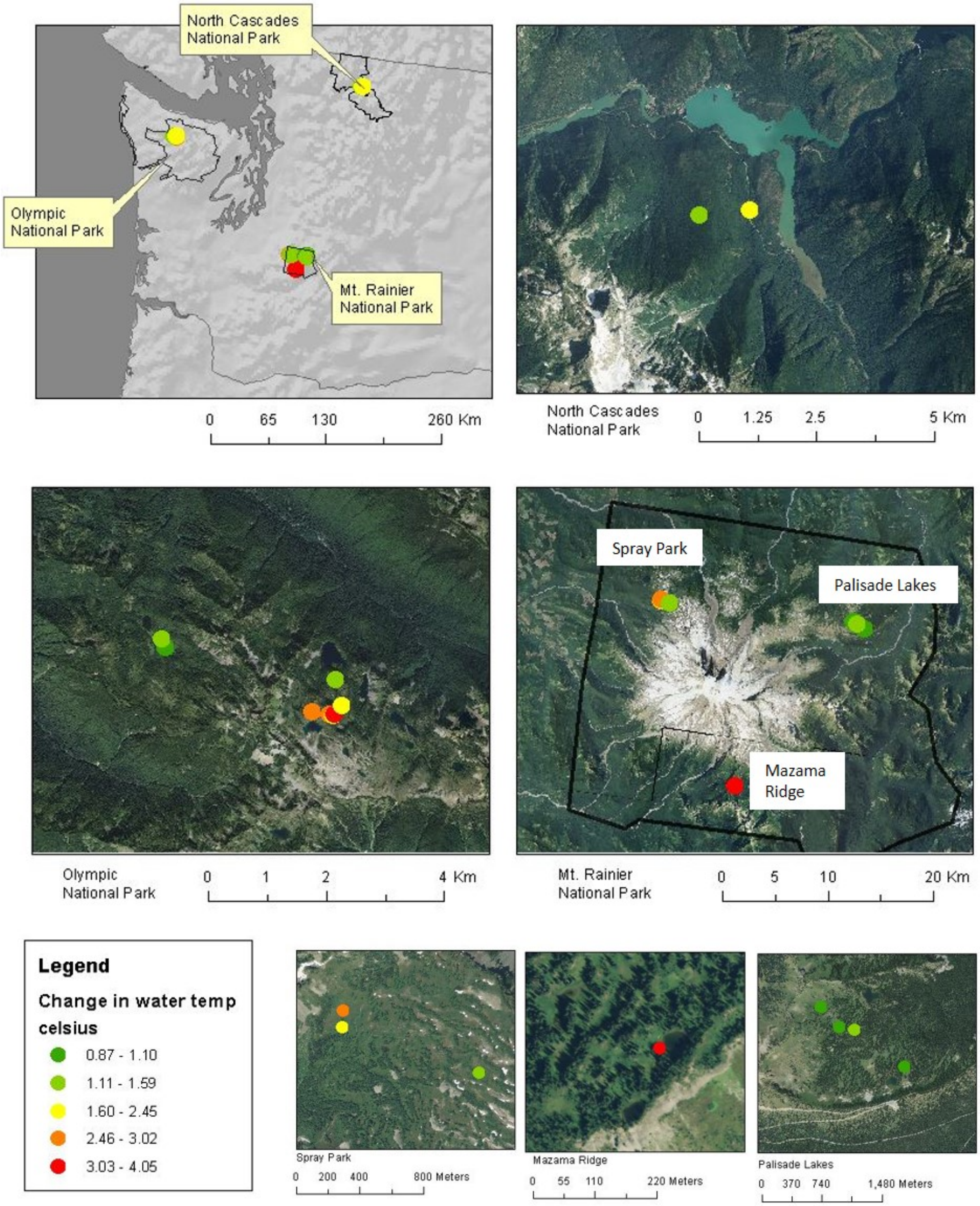


Figure 3.3.15. Focal sites of water temperature monitoring and climate change simulations of water temperature in North Cascades, Olympic, and Mount Rainier National Parks.

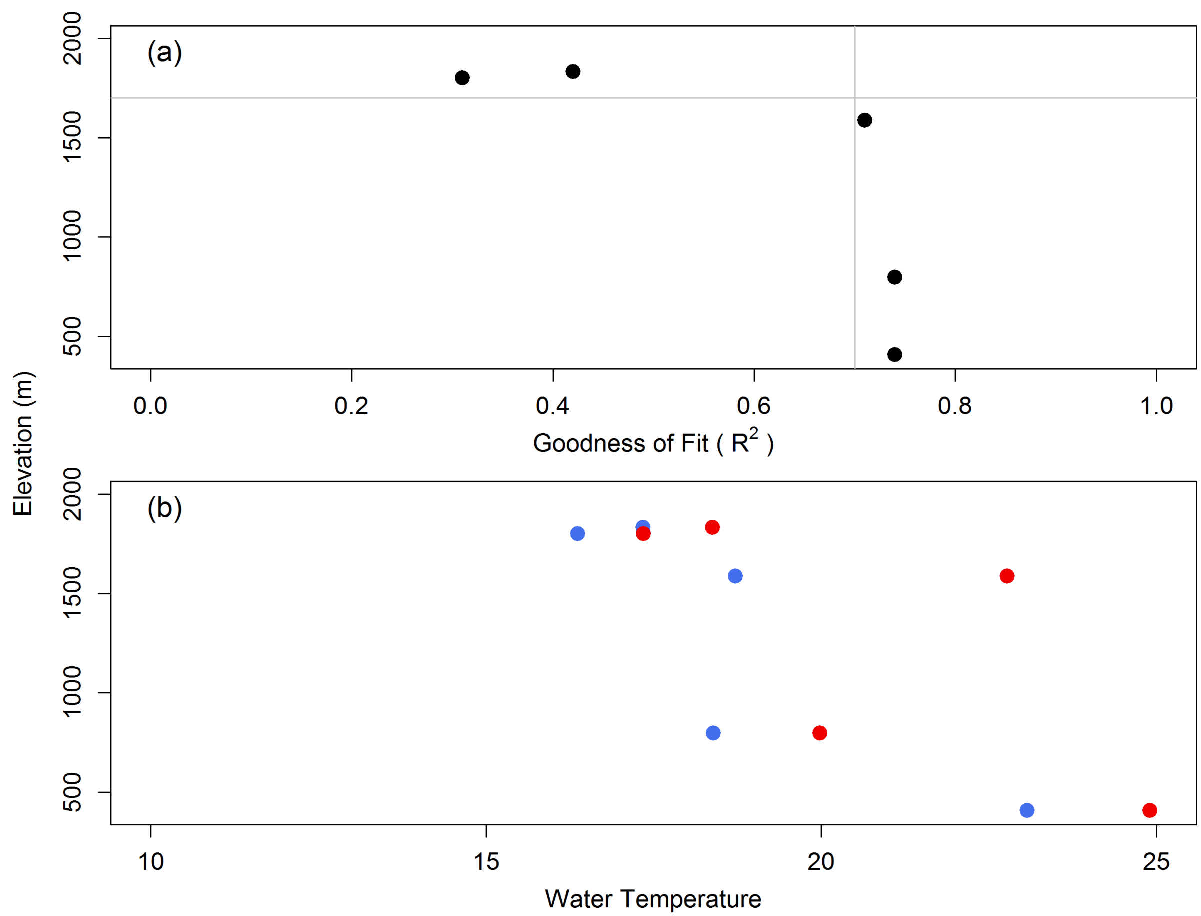


Figure 3.3.16. Goodness of fit values (a) for a set of permanent ponds across an elevational gradient. Panel (b) shows historical water temperature values in blue, and projected 2080s values in red.

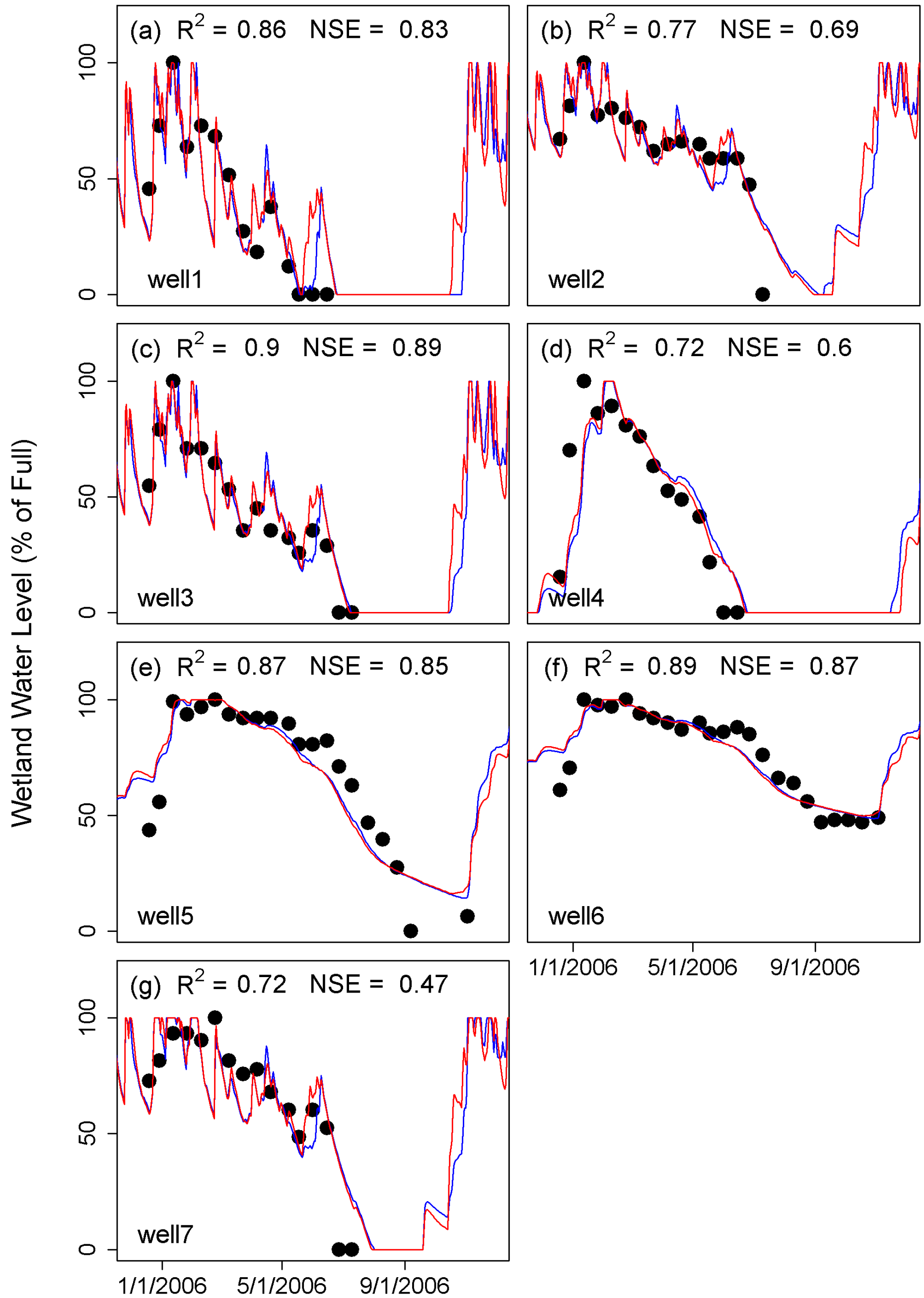
Puget Lowlands Wetlands

Either soil moisture in middle or bottom layer was the best predictor for Puget lowlands wetlands (Table 3.3.2). The goodness of fit showed that regression models fairly successfully reconstructed the historical patterns observed during December 2005 and November 2006: $R^2 > 0.72$ and NSE > 0.42 (Figure 3.3.12 and Table 3.3.2). Based on the wetland classification developed for montane wetlands, there are three ephemeral, three intermediate and one perennial wetland represented by these wells. Unlike montane wetlands that show significant impacts of climate change on wetland hydrology such as reduced water levels, rapid drawdown, and a longer dry season, projections for these Puget lowlands sites show no significant impact of climate change (Table 3.3.3 and Figure 3.3.12).

Table 3.3.2 Summary of simulated wetland depth for Puget Lowlands wetlands.

Name	Predictor	Goodness of Fit		Averege Min Water depth (% of full)		Type
		R^2	NSE	Historical	2080s	
well1	soilm2	0.86	0.83	0.0	0.0	ephemeral
well2	soilm2	0.77	0.69	11.0	7.6	intermediate
well3	soilm2	0.90	0.89	0.1	0.1	ephemeral
well4	soilm3	0.72	0.60	0.0	0.0	ephemeral
well5	soilm3	0.87	0.85	20.9	21.4	intermediate
well6	soilm3	0.89	0.87	52.4	52.7	perennial
well7	soilm2	0.72	0.47	3.6	2.2	intermediate

Figure 3.3.12. Observed water depths during Dec. 2005-Nov. 2006 for Puget Lowlands wetlands (solid circles) compared with the simulated wetland water depths using the regression model that were developed for historical (blue lines) and for the 2080s (red lines).



Columbia Plateau Wetlands

Historical reconstruction of wetland dynamics

For the Columbia Plateau wetlands, the soil moistures in the top and bottom soil layers were better correlated with observed wetland surface area than other water balance variables (Fig. 3.3.13). Using these two best predictors, we developed a multivariate regression model for the calibration period (1996-2011) (daily-based model). Since not all wetlands had a good fit with the daily-based multivariate regression model, we also developed a regression model using cool season precipitation and annual minimum water level observations (annually-based model) to test the fit between observed wetland data and this alternative model. As described above, we divided our wetlands into four groups based on model fits (or lack thereof), which may reflect relationships with different putative hydrologic drivers. Again, it is important to note that, due to the limited field data for Columbia Plateau wetlands and the complex and potentially strong human influences on hydrology, our classifications should be understood as initial hypotheses to be tested and further explored, rather than formal classifications based on defensible hydrologic mechanisms.

Group 1 wetlands were those whose R and NSE values for both the calibration and validation periods were greater or equal to 0.5 and -2.0, respectively, and had a ratio of greater or equal to 0.8 between the range of simulations and that of observed data. Group 2 were wetlands that did not satisfy this criterion, but had R values for the regression models using cool precipitation and annual minimum water level observations of greater or equal to 0.7. If wetlands did not satisfy criteria for Groups 1 and 2 but showed anomalously high or low values for a certain period, we classified them in Group 3. All remaining wetlands were classifed as Group 4. Box plots showing the correlation coefficients for each group are shown in Figure 3.3.14. The thresholds were chosen based on the distribution of the data.

Since Groups 1 and 2 are defined based on model fit, the two measures of goodness of fit (Nash Sutcliffe efficiency (NSE) and the Pearson's correlation coefficient (R)) show that regression models match empirical observations reasonably well for those groups (Group 1: n=192; Group 2: n=50). For Group 1, there was not a significant difference in model fits between the daily multivariate soil moistures regression model and the annual cool season precipitation model. Group 2 did show a significantly better fit to the annual model (Figure 3.3.14). For a majority of sites (535/772), however, empirical observations did not match either the daily multivariate soil moistures regression model or the annual cool season precipitation model (Group 3, n=185; Group 4, n=350). While we can hypothesize that Group 3 reflects human influences on hydrology, we do not know the driving mechanisms differentiating the

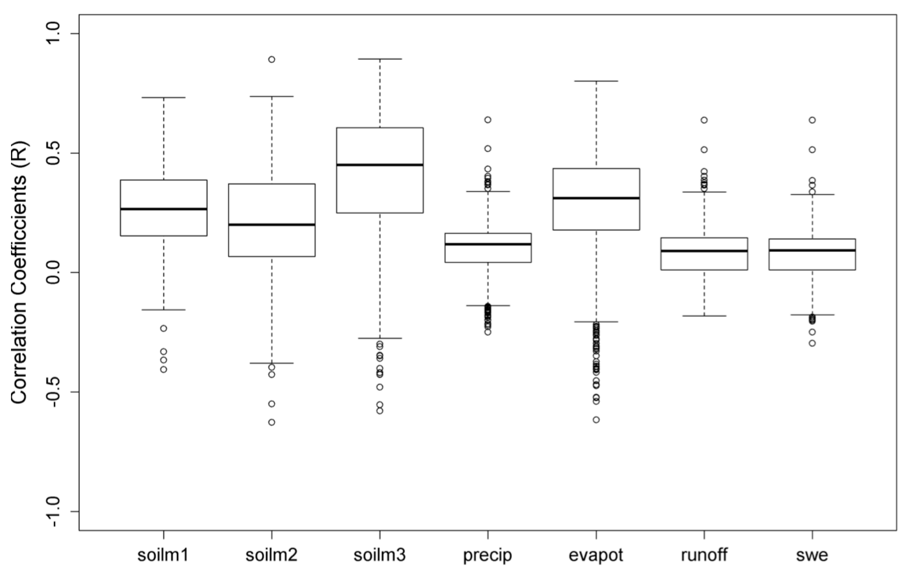


Figure 3.3.13. Correlation coefficients between observed water surface areas for 772 Columbia Plateau wetlands obtained from remote sensing and simulated water balance variables such as soil moistures in the top (soilm1), middle (soilm2), and bottom (soilm3) layers, precipitation (precip), evapotranspiration (evapot), runoff, and snow water equivalent (swe).

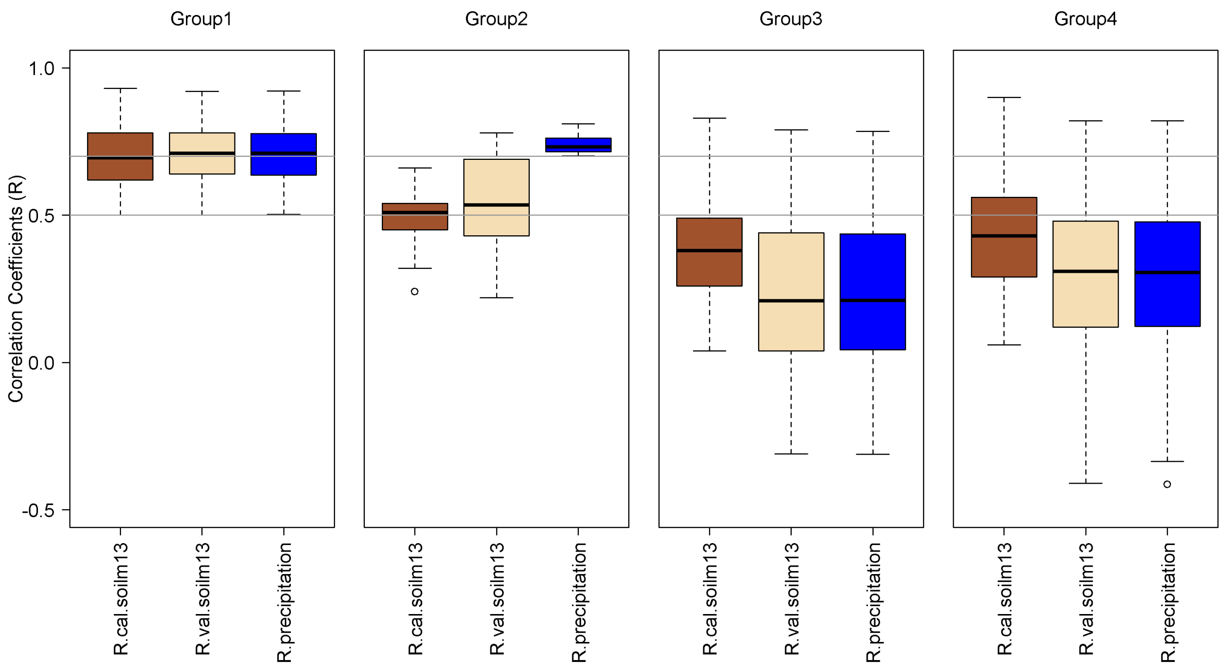


Figure 3.3.14 Correlation coefficients (Pearson's R) between observed water surface areas for Columbia Plateau wetlands using the daily-based multivariate regression model during calibration (R.cal daily) and validation (R.val daily) and using the annually-based regression model (R.annually) broken out by Groups. Horizontal lines denote R values of 0.5 and 0.7.

Groups. Figures 3.3.15-3.3.19 show examples of wetlands and their fits to the two regression models. For example, for the sites depicted in Figure 3.3.15, the simulated multivariate regression model reasonably well captures the range and pattern of annual and inter-annual variation present. In Figure 3.3.16, the daily-based multivariate model misses significant decadal-or-longer fluctuations in wetland water levels (upper panels), but these are reasonably captured by the annually-based cool season precipitation model (lower panels). Figures 3.3.17-19 illustrate poor fits to both models for a selection of representative Group 3 and 4 wetlands. We discuss potential drivers of these differences in the Findings section (Section 4) below. Figure 3.3.20 shows the geographic distribution of Groups 1 and 2 across our three focal field regions of the Columbia Plateau.

Groups 1 and 2 do not align smoothly with our ephemeral-to-permanent hydrologic classification. For example, if classified based on their hydrologic patterns using the same criteria as for montane wetlands described above, Group 1 includes 21 ephemeral, 159 intermediate, and 12 perennial wetlands. Group 2, likewise classified, contains 24 intermediate, 15 perennial, and 1 permanent wetland.

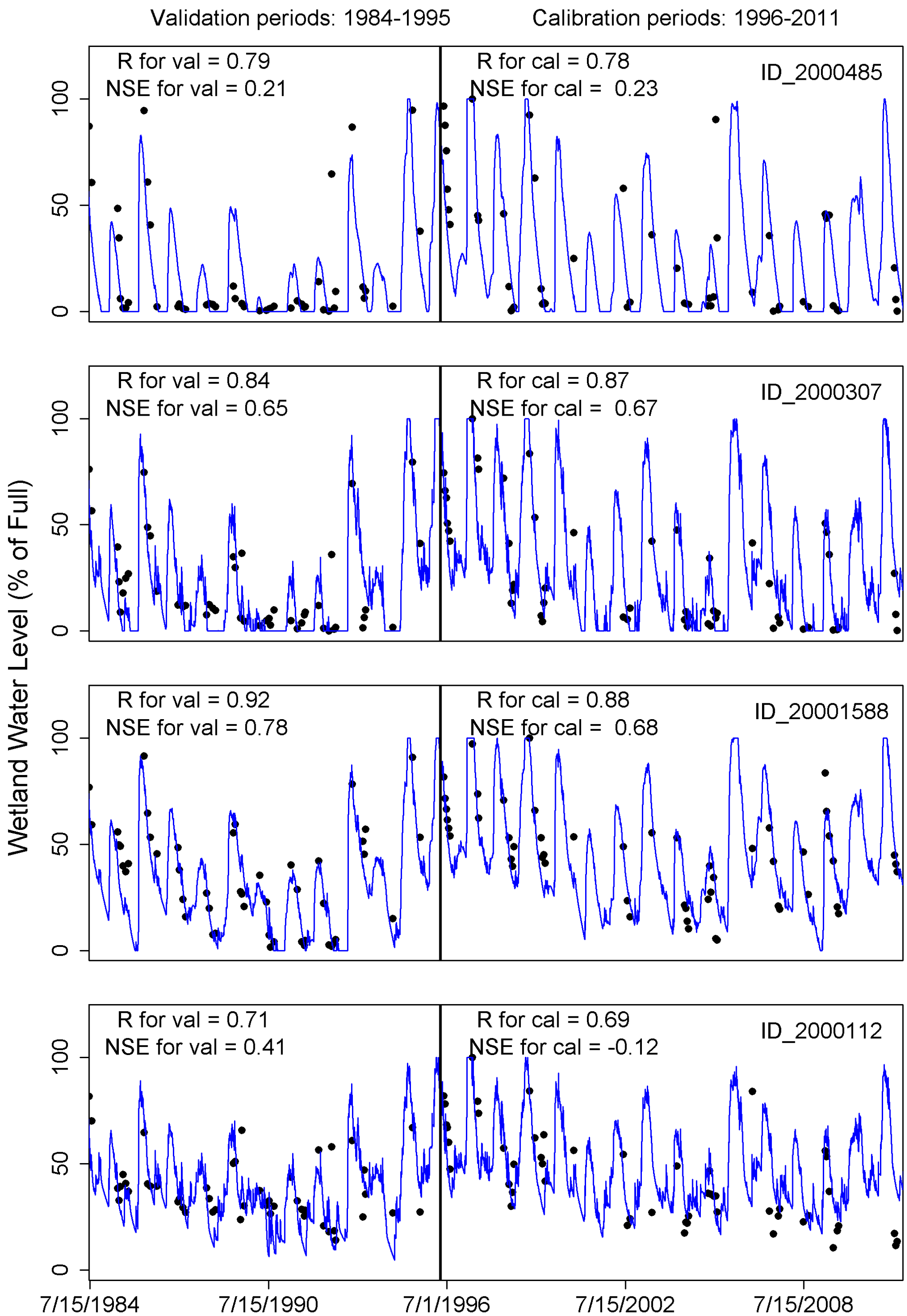


Figure 3.3.15. Group 1, observed wetland water surface areas for 1984-2011 (solid circles) compared with the simulated wetland water surface area using the daily-based multivariate regression models that were developed during calibration period (1996-2011) (blue lines). Black line denotes the boundary between calibration and validation periods. R and NSE values were calculated both calibration and validation periods.

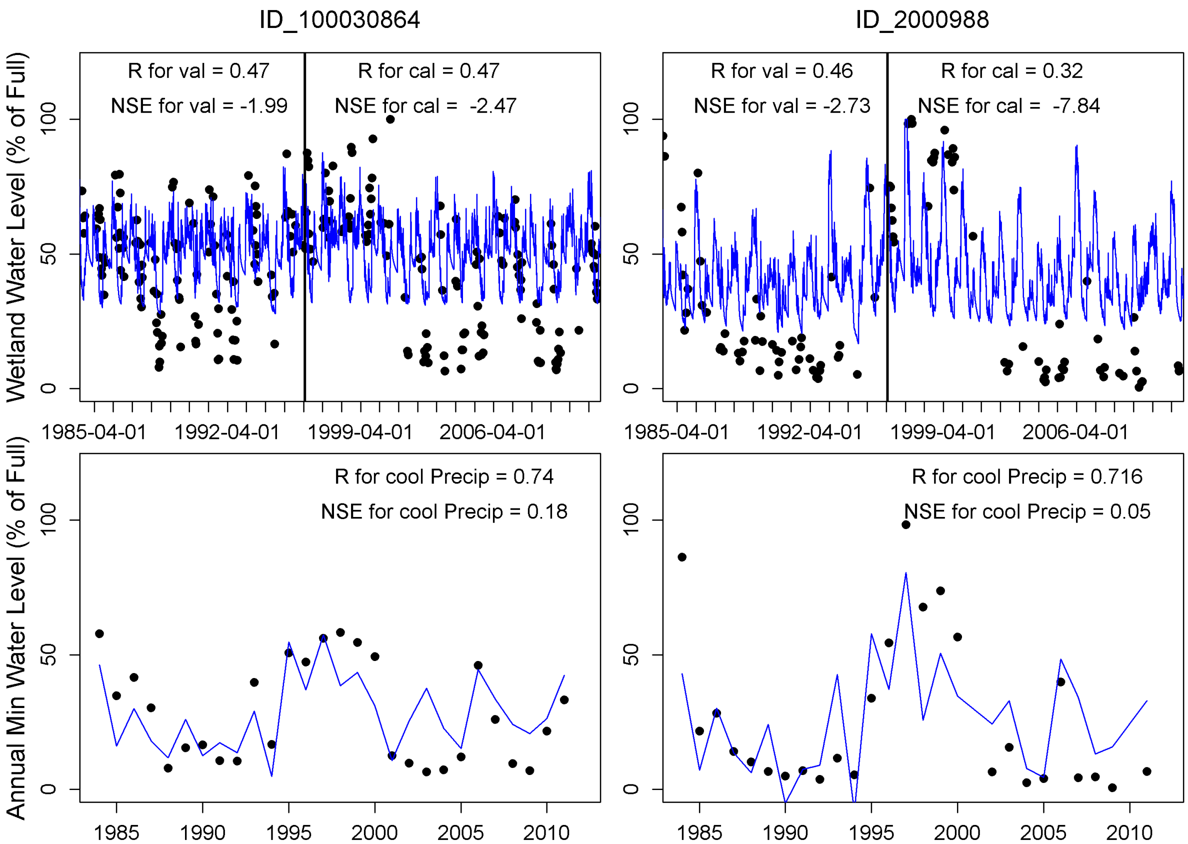


Figure 3.3.16. Plots of two representative wetlands in Group 2. Top panels: Observed wetland water surface areas for 1984-2011 (solid circles) compared with the simulated wetland water surface area using the daily-based multivariate regression models that were developed during calibration period (1996-2011) (blue lines). Black line denotes the boundary between calibration and validation periods. Bottom panels: Observed annual minimum water surface areas for 1984-2011 (solid circles) compared with simulated wetland water surface area using the regression model based on cool season precipitation (annually-based) for 1984-2011 (annually-based) (blue lines). R and NSE values were calculated both calibration and validation periods.

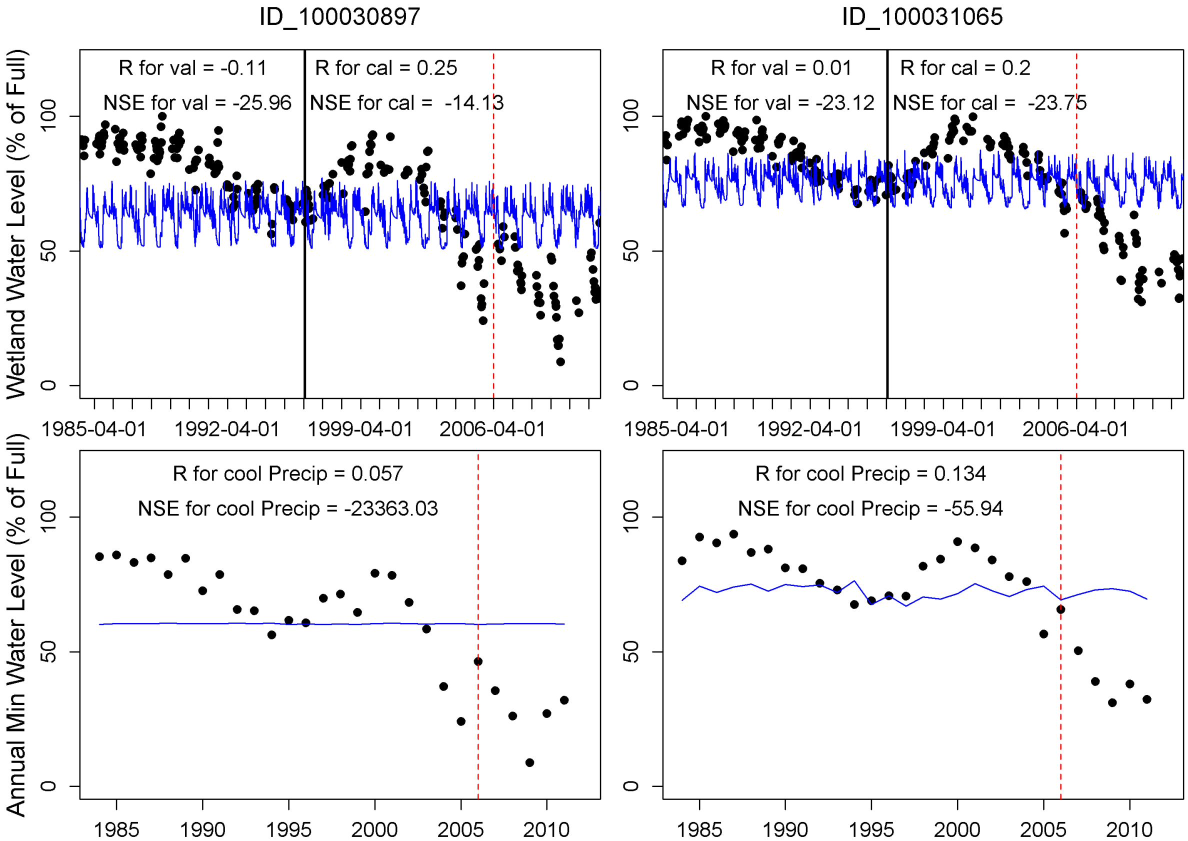


Figure 3.3.17. Group 3 wetlands that show unusually low wetland water levels after year 2006 (dotted red line). Top panels: Observed wetland water surface areas for 1984-2011 (solid circles) compared with the simulated wetland water surface area using the daily-based multivariate regression models that were developed during calibration period (1996-2011) (blue lines). Black line denotes the boundary between calibration and validation periods. Bottom panels: Observed annual minimum water surface areas for 1984-2011 (solid circles) compared with simulated wetland water surface area using the regression model based on cool season precipitation (annually-based) for 1984-2011 (annually-based) (blue lines). R and NSE values were calculated both calibration and validation periods.

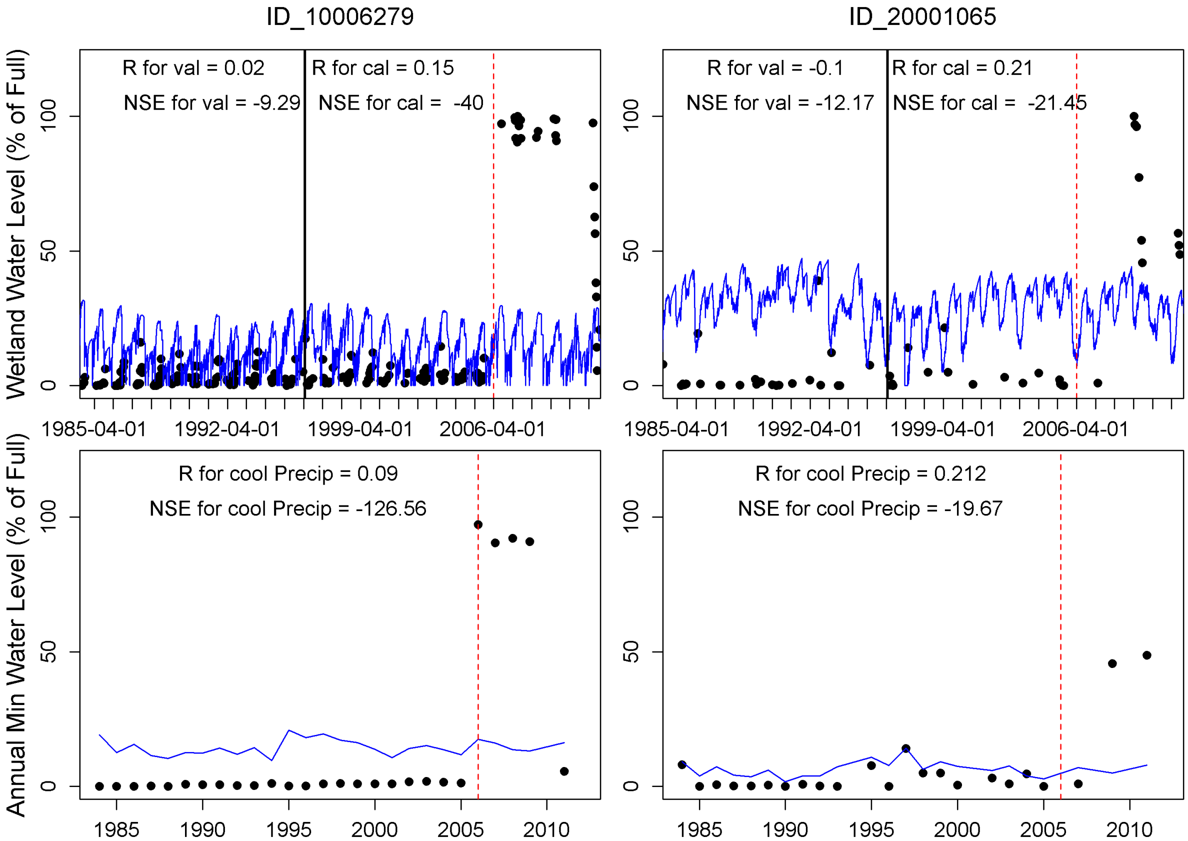


Figure 3.3.18. Group 3 wetlands that show unusually high wetland water levels after year 2006 (dotted red line). Top panels: Observed wetland water surface areas for 1984-2011 (solid circles) compared with the simulated wetland water surface area using the daily-based multivariate regression models that were developed during calibration period (1996-2011) (blue lines). Black line denotes the boundary between calibration and validation periods. Bottom panels: Observed annual minimum water surface areas for 1984-2011 (solid circles) compared with simulated wetland water surface area using the regression model based on cool season precipitation (annually-based) for 1984-2011 (blue lines). R and NSE values were calculated both calibration and validation periods.

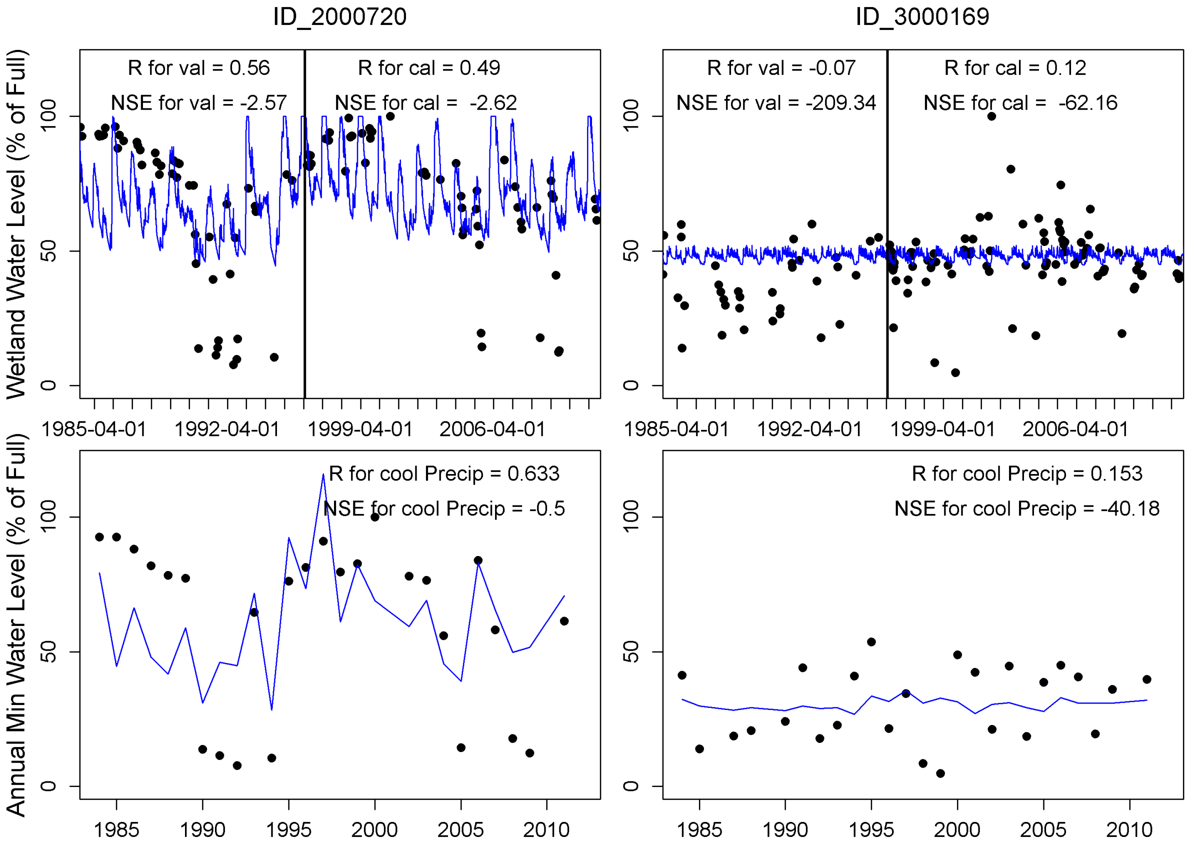


Figure 3.3.19. Group 4 wetlands that show unusually high wetland water levels after year 2006 (dotted red line). Top panels: Observed wetland water surface areas for 1984-2011 (solid circles) compared with the simulated wetland water surface area using the daily-based multivariate regression models that were developed during calibration period (1996-2011) (blue lines). Black line denotes the boundary between calibration and validation periods. Bottom panels: Observed annual minimum water surface areas for 1984-2011 (solid circles) compared with simulated wetland water surface area using the regression model based on cool season precipitation (annually-based) for 1984-2011 (annually-based) (blue lines). R and NSE values were calculated both calibration and validation periods.

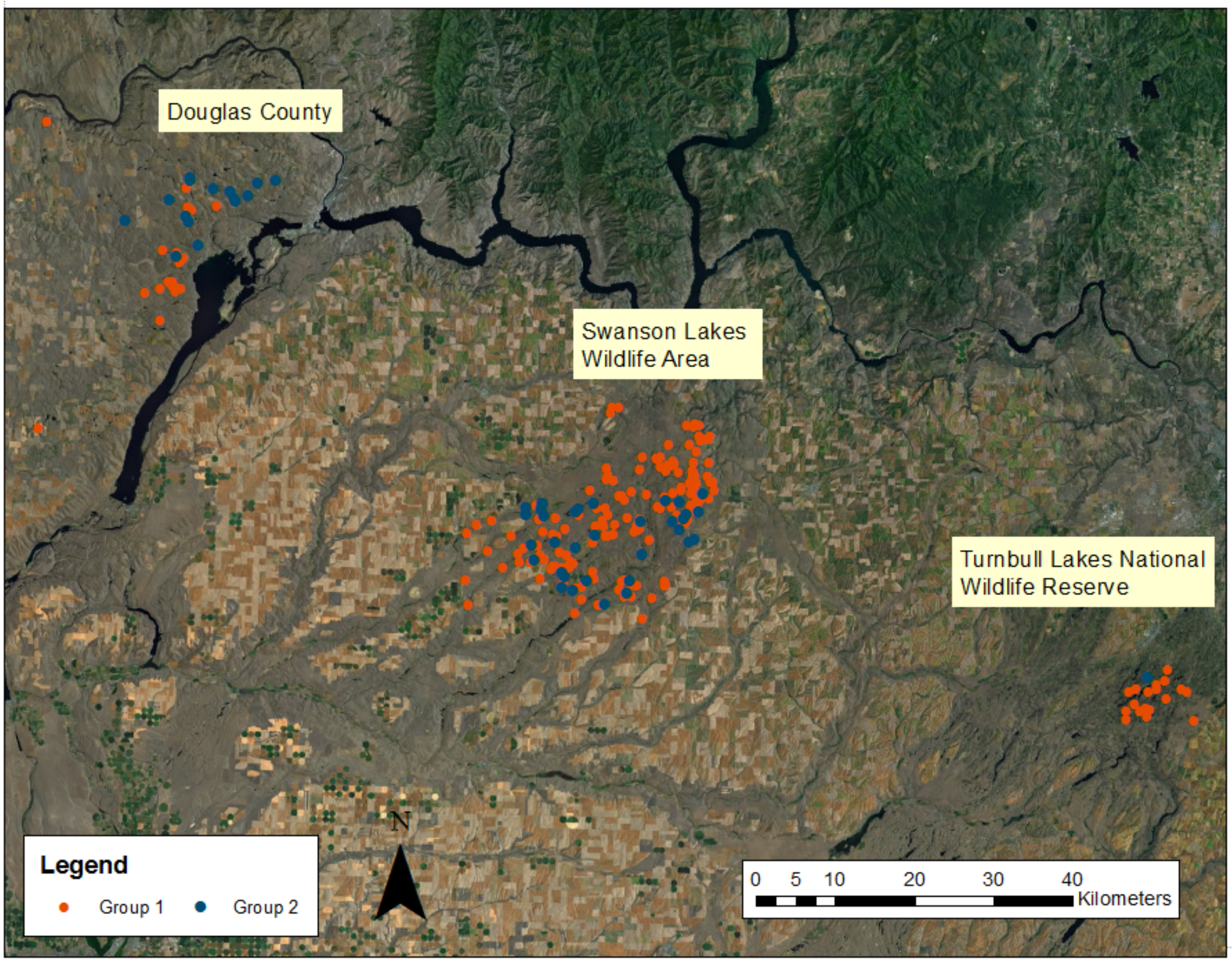


Figure 3.3.20. Map of Group 1 and Group 2 wetland locations. Group 1 wetlands had a stronger correlation with the top and bottom soil moisture layers of the VIC model. Group 2 wetlands were more strongly correlated with average annual cool season precipitation.

Future climate projections of wetland dynamics

Overall, Group 1 wetlands show a slight to moderate reduction in surface area that might indicate reduction in water levels in the 2080s for ephemeral and intermediate wetlands, and a very slight average increase for perennial ponds (Table 3.3.3) with no significant difference overall in wetland water levels in the 2080s compared to the historical period (Figures 3.3.21-3.3.22). In contrast, all wetland types show a slight (not statistically significant) increase in water levels for Group 2 sites (Figures 3.3.23-3.3.24; Table 3.3.3). The poor ability of the VIC model to reconstruct historical dynamics of Group 3 and 4 wetlands means that any projections of future climate impacts on these sites based on the VIC model are not currently well supported. Therefore we did not develop climate change projections for these wetlands.

Table 3.3.3 Relationship between observed hydrologic class and Group 1 and 2 assignment based on goodness of fit to VIC simulations. Groups 3 and 4 are not depicted because their hydrographs are aberrant in various ways that do not allow confident assignment, and the historical model fits are too poor to enable rigorous climate projections.

Group	Type	Number of Wetlands	Average Minimum Water Levels (% of full)	
			Historical	2080s
Group 1	ephemeral	21	1.52	0.94
	intermediate	159	6.47	5.77
	perennial	12	36.32	37.06
Group 2	intermediate	24	24.3	29.7
	perennial	25	44.3	50.1
	permanent	1	77.06	79.06

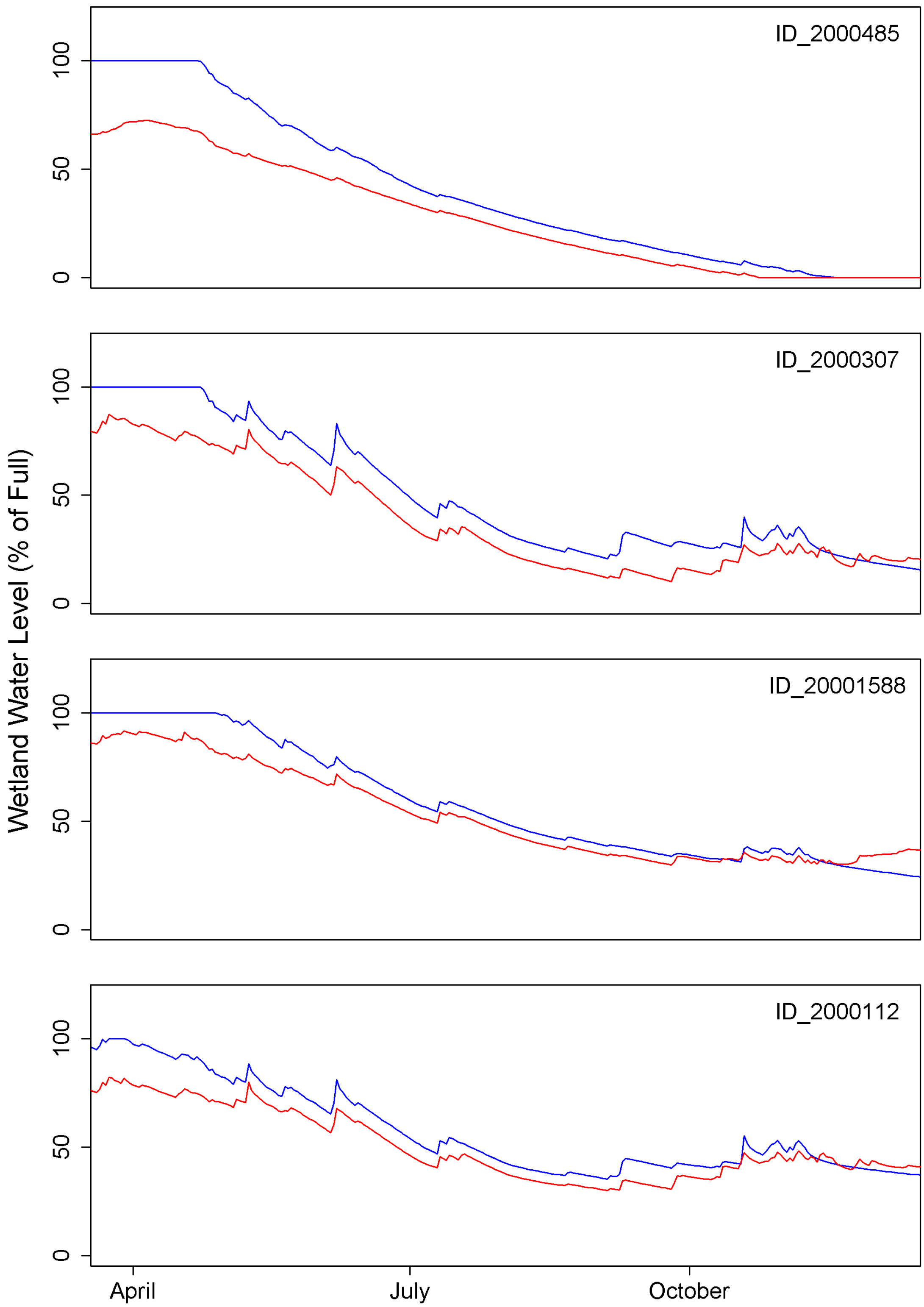


Figure 3.3.21. Projected wetland response to climate change for Group 1 in Columbia Plateau. Blue solid lines are wetland hydrographs for year 1984 and red lines show wetland hydrographs of year 1984 with climate change perturbation for the 2080s.

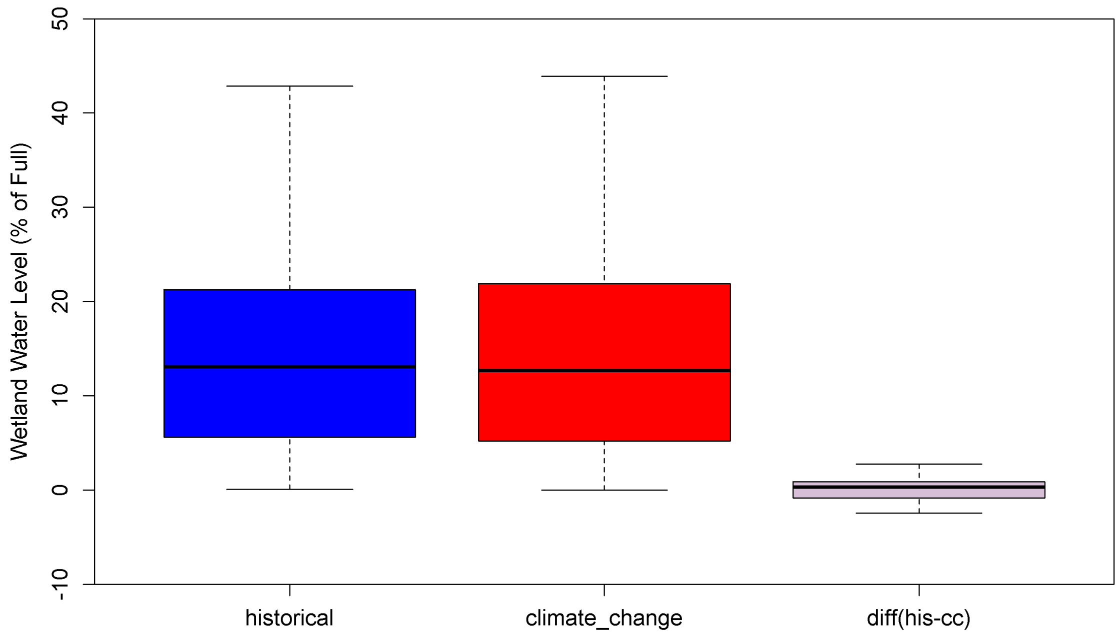


Figure 3.3.22. Boxplots of annual water levels for historical, 2080s, and the difference between historical and climate change for Group 1 wetlands. There is no significant change in wetland minimum water levels for the 2080s.

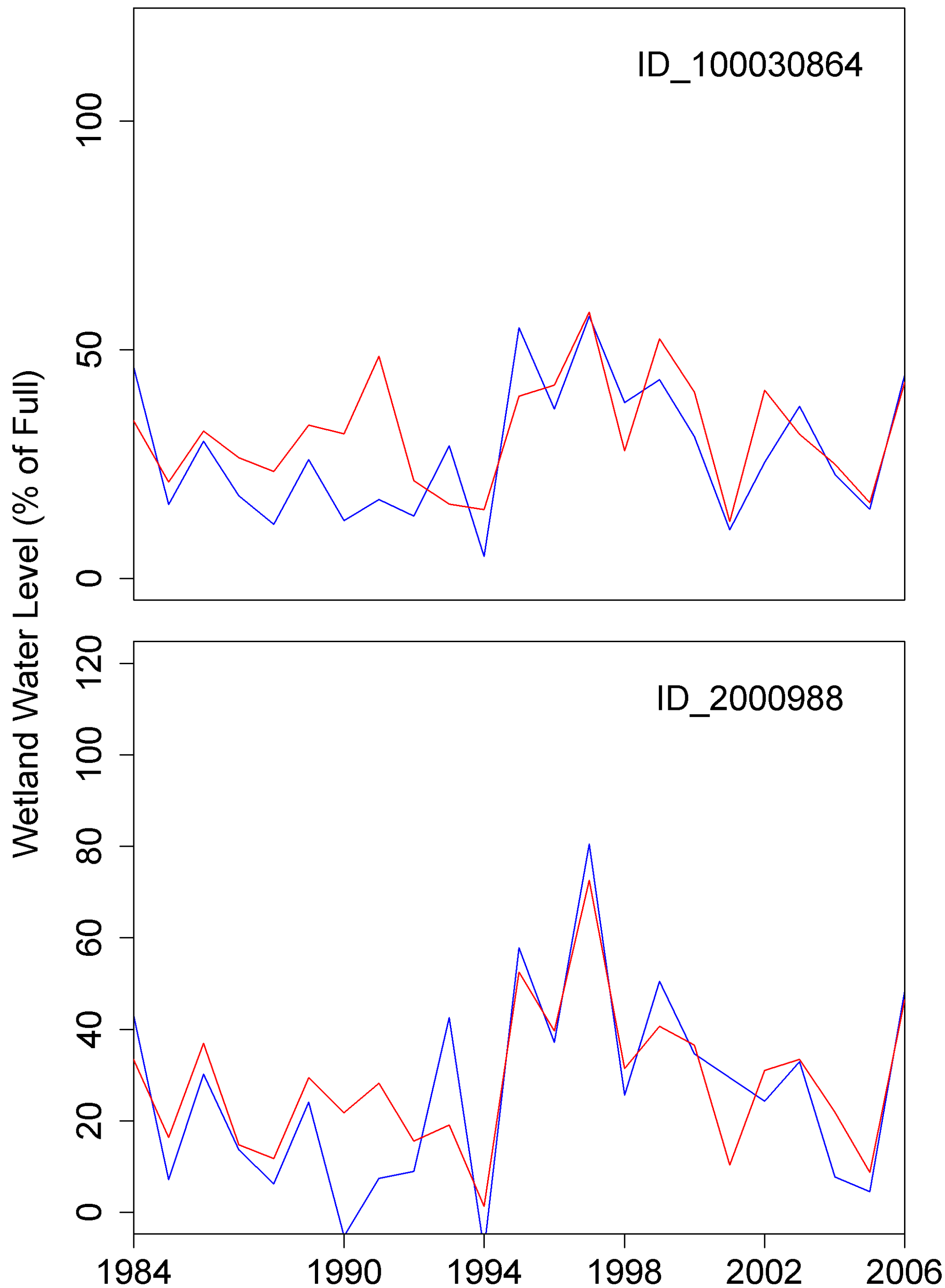


Figure 3.3.23. Projected wetland response to climate change for Group 2 wetlands in the Columbia Plateau. Blue solid lines are wetland hydrographs for year 1984 and red lines show wetland hydrographs of year 1984 with climate change perturbation for the 2080s. Minimum water levels are slightly higher for the 2080s in comparison to historical runs because of projected slight increase in cool season precipitation.

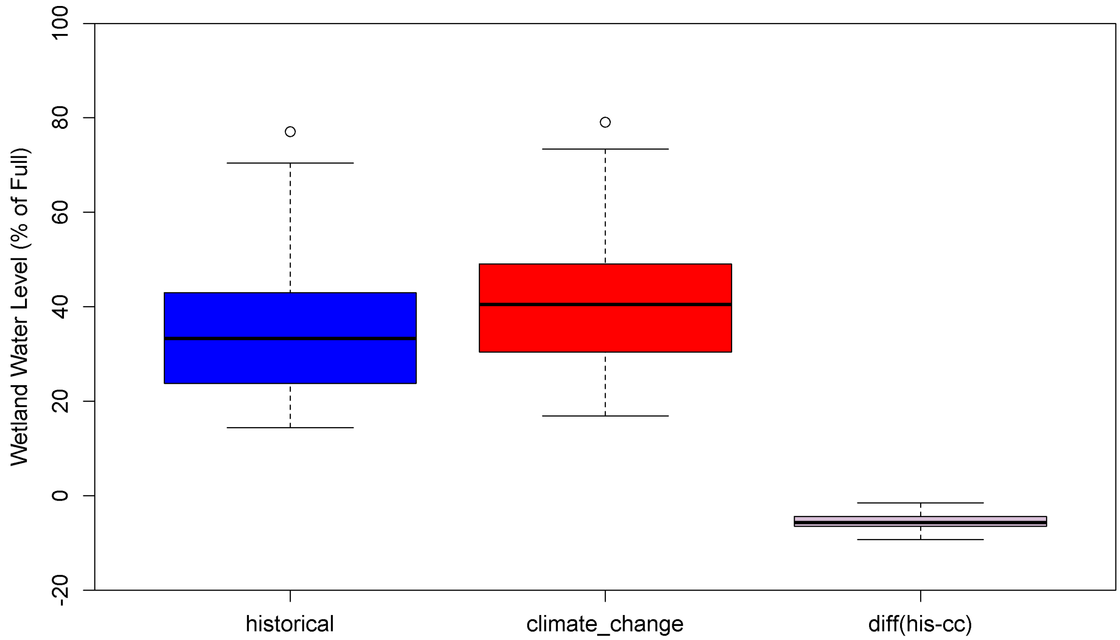


Figure 3.3.24. Boxplots of annual water levels for historical, 2080s, and the difference between historical and climate change for Group 2 wetlands, using cool season precipitation as a predictor. Wetland minimum water levels are projected to slightly increase for the 2080s due to projected increase in precipitation.

3.4 Ecological Modeling

Montane Wetlands

Maximum pond depth was highly correlated with both maximum size (Spearman correlation coefficient = 0.80) and maximum percent shallows (-0.82), so we conducted a principal component analysis (PCA) on these three variables. The first PCA axis carried the majority of the loadings with a straightforward interpretation. Lower PCA values are bigger, deeper ponds with less shallows, while higher PCA values are smaller ponds with more shallows. We therefore used the first PCA axis in our logistic regression analyses in place of maximum pond depth,

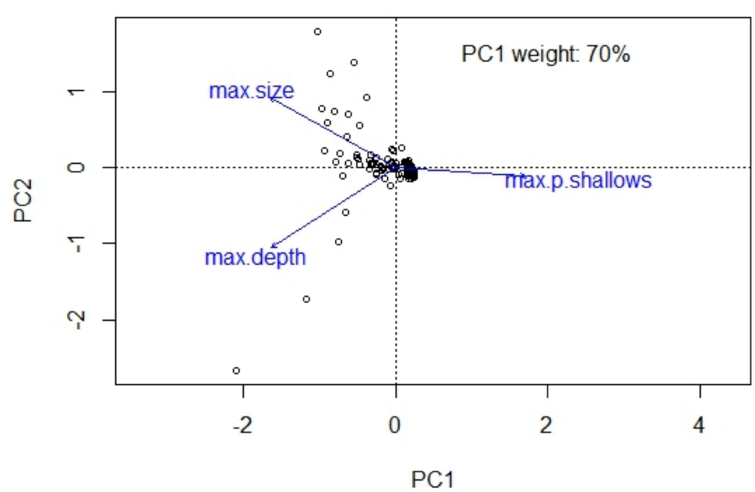


Figure 3.4.1 First and second axis of principal components analysis on pond max size, max depth, and percent shallows.

percent shallows, and maximum pond size, which we removed from the analyses.

Rana cascadae (Cascades frog): breeding evidence

For Cascades frog breeding evidence, AIC model selection produced a set of 55 models that held 95% of the weight from the candidate set of 210 models. No single top model was supported: ΔAIC_{max} = 8.26, and maximum w_{Ak} = 0.15. Table 3.4.1 shows the top ranked models with $\Delta AIC_c < 4$. (ΔAIC_c of 2-4 is considered positive evidence of one model having a superior fit.) Hydroperiod class and elevation had the highest variable importance, as they were both included in the majority of top models (Figure 3.4.2). These were also the only two variables with significant parameter coefficient estimates, suggesting a higher incidence of Cascades frog breeding in intermediate and perennial ponds (relative to fast-drying ephemeral ponds) (Figure 3.4.3, Table 3.4.2). Fish had the third highest variable importance. The parameter coefficient estimates suggest that, despite being non-significant (Table 3.4.2), this factor may have a large influence on whether or not *R. cascadia* breeds in a given pond. The lack of significance of this variable may be attributable to the small sample size of ponds

Rana cascadae embryo inside an eggmass in a montane pond in Olympic National Park.

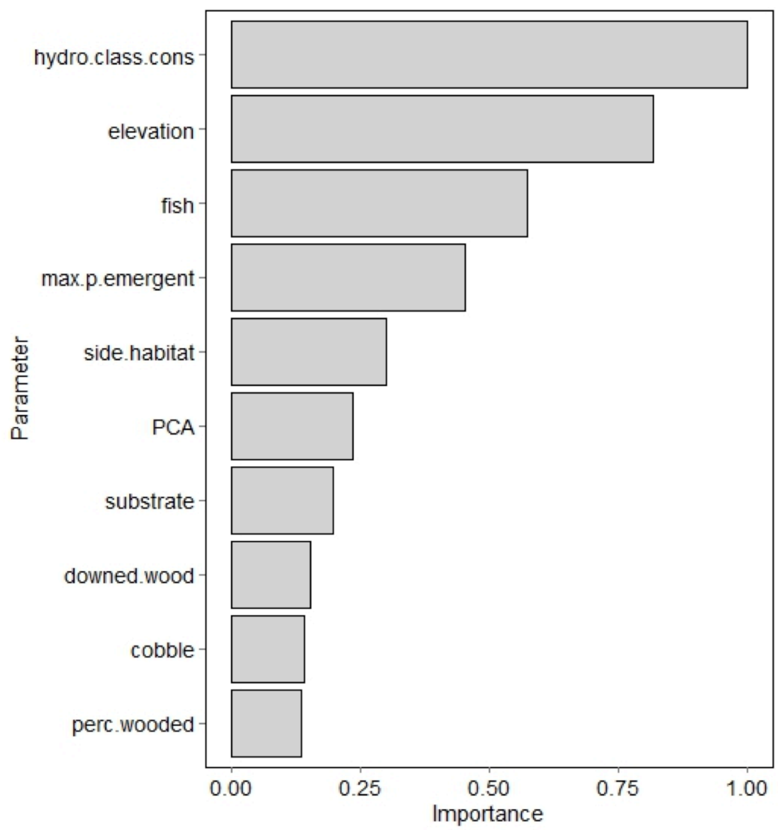


Figure 3.4.2 Relative ranking of variable importance for parameters included in the set of models holding 95% of the weight of support based on Akaike weights for *Rana cascadae* breeding evidence. Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.

with fish presence in this dataset (n = 9/168), all of which are in the permanent hydroperiod class.

Table 3.4.1. Top ranked models with $\Delta AIC_c < 4$ for *Rana cascadae* breeding evidence (BE). *elev* = elevation, *hydro* = hydroperiod, *emergent* = maximum percent of pond occupied by emergent vegetation, *fish* = fish presence, *side habitat* = presence of complex inlet or adjacent wetland habitat, *substrate* = pond bottom substrate, *PCA* = first axis of PCA, *cobble* = presence of cobbles in the substrate, *wooded* = percent of pond perimeter occupied by woods. For full set of top 55 models holding 95% of all model support, see Appendix D.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	208.8	BE ~ *elev* + *hydro* + *emergent* + *fish*	0	0.15
2	209.4	BE ~ *elev* + *hydro* + *fish* + *side habitat*	0.56	0.11
3	210.9	BE ~ *elev* + *hydro* + *substrate* + *fish*	2.09	0.05
4	211.0	BE ~ *elev* + *hydro* + *PCA* + *emergent*	2.16	0.05
5	211.2	BE ~ *elev* + *hydro* + *cobble* + *fish*	2.39	0.04
6	211.2	BE ~ *elev* + *hydro* + *PCA* + *fish*	2.43	0.04
7	211.4	BE ~ *elev* + *hydro* + *wooded* + *fish*	2.57	0.04
8	211.6	BE ~ *elev* + *hydro* + *fish* + *downed wood*	2.75	0.04
9	211.6	BE ~ *elev* + *hydro* + *emergent* + *side habitat*	2.82	0.04
10	211.9	BE ~ *elev* + *hydro* + *PCA* + *side habitat*	3.11	0.04
11	212.1	BE ~ *hydro* + *emergent* + *fish* + *side habitat*	3.30	0.03
12	212.4	BE ~ *elev* + *hydro* + *emergent* + *downed wood*	3.60	0.02

Table 3.4.2. Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels for *Rana cascadae* breeding. Variable codes are defined in Table 3.4.1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
*Intercept**	-1.79 (-3.20, -0.38)	0.717
*elevation**	-0.47 (-0.87, -0.07)	0.204
PCA	0.34 (-0.24, 0.92)	0.296
emergent	0.34 (-0.04, 0.72)	0.193
cobble(yes)	-0.14 (-0.97, 0.69)	0.425
wooded	0.08 (-0.32, 0.49)	0.207
fish(yes)	-2.09 (-4.59, 0.42)	0.278
*hydro(intermediate)**	2.14 (0.88, 3.41)	0.645
*hydro(perennial)**	1.62 (0.50, 2.74)	0.569
hydro(permanent)	0.80 (-0.45, 2.06)	0.642
side habitat(yes)	0.57 (-0.26, 1.40)	0.423
downed wood(yes)	-0.29 (-1.14, 0.56)	0.434
substrate(muck)	1.48 (-0.18, 3.15)	0.850
substrate(mud.clay.silt)	0.96 (-0.71, 2.64)	0.852
substrate(sand.gravel)	1.75 (-0.34, 3.84)	1.067

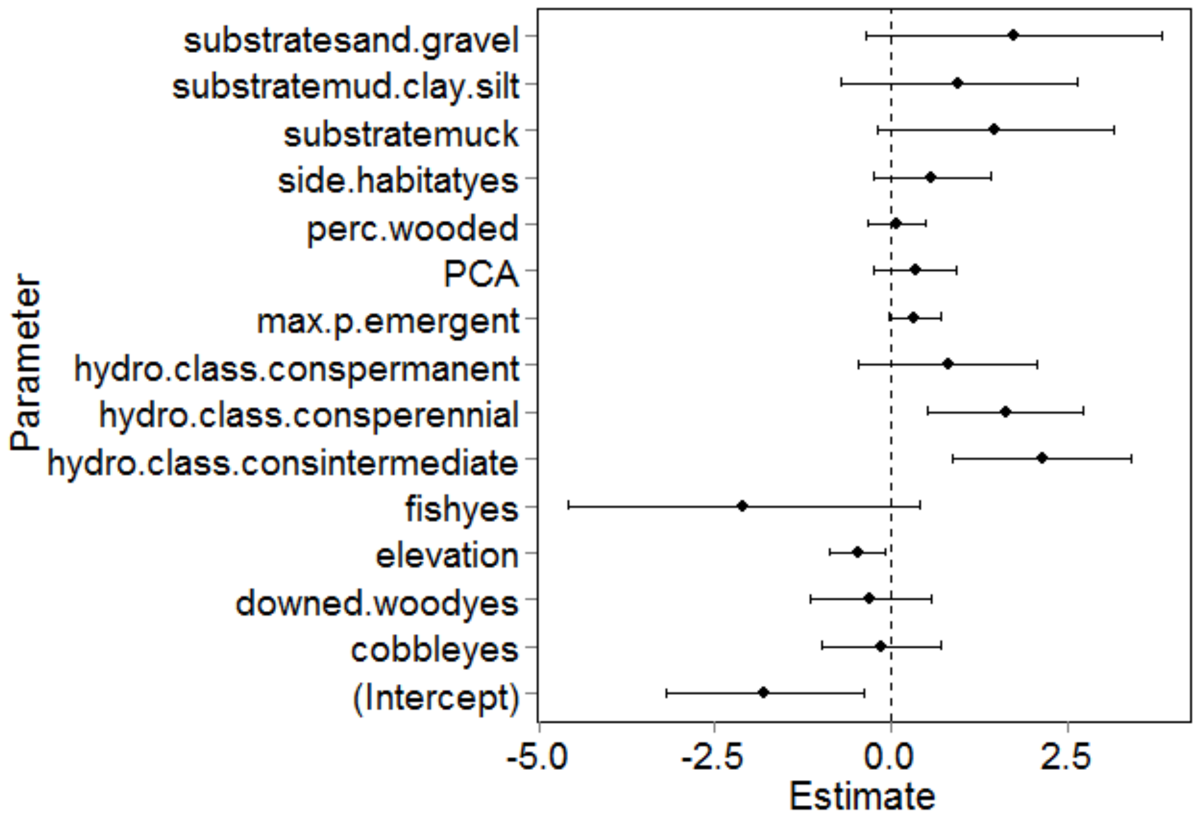


Figure 3.4.3 Scaled and centered model-averaged parameter coefficient estimates for the variables included in the set of models holding 95% of the weight of support based on Akaike weights for *Rana cascadae* breeding evidence. Hydro.class estimates are in reference to ephemeral wetlands.

Rana cascadae (Cascades frog): adult presence

Rana cascadae adult in a perennial montane pond in Olympic National Park.

For Cascades frog adult presence, AIC model selection produced a set of 11 models that held 95% of the weight from the candidate set of 210 models. The top model had relatively strong support (ΔAIC_c for second-ranked model = 2.83; ΔAIC_{max} = 8.59; maximum w_{Ak} = 0.59; Table 3.4.3). The top model included hydroperiod class, the first PCA axis (a measure of pond shape or bathymetry), the percent of wooded perimeter, and fish presence, all of which had significant parameter coefficient estimates (Figure 3.4.4-5 and Table 3.4.4). Pond shape (PCA) and wooded perimeter had the highest variable importance and were included in all top models, showing an association between Cascades frogs adults and smaller, shallower ponds (higher PCA values) with greater forest cover. These variables were followed in importance by fish and hydroperiod (Figure 3.4.4). Adult Cascades frogs were most strongly associated with intermediate and permanent ponds (relative to fast-drying ephemeral ponds) (Figure 3.4.5 Table 3.4.4). In this case fish had a significant negative influence on the presence of adult *Rana cascadae* (Table 3.4.4) despite the small number of sites in which they were present (n=9/168).

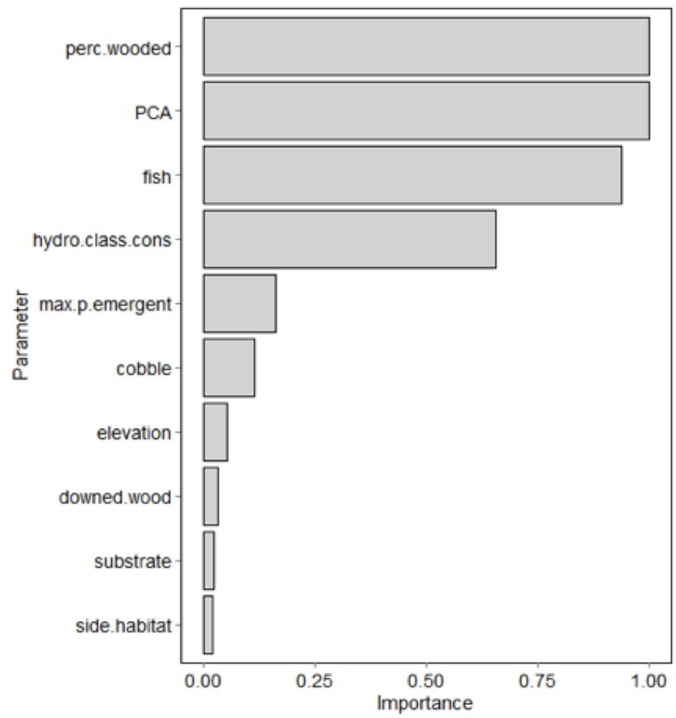


Figure 3.4.4 Relative ranking of variable importance for parameters included in the set of models holding 95% of the weight of support based on Akaike weights for *Rana cascadae* adult presence. Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.

Table 3.4.3 Top ranked models for the set of models holding 95% of all model support for *Rana cascadae* adult presence (AP*).* *elev* = elevation, *hydro* = hydroperiod, *PCA* = first PCA axis, *wooded* = percent of pond perimeter occupied by woods, *fish* = fish presence, *emergent* = maximum percent of pond occupied by emergent vegetation, *side habitat* = presence of complex inlet or adjacent wetland habitat, *substrate* = pond bottom substrate, *cobble* = presence of cobbles in the substrate, *downed wood* = presence of branches and downed wood in the pond.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	165.3	AP ~ *hydro* + *PCA* + *wooded* + *fish*	0	0.59
2	168.2	AP ~ *PCA* + *emergent* + *wooded* + *fish*	2.83	0.14
3	169.0	AP ~ *PCA* + *wooded* + *cobble* + *fish*	3.68	0.09
4	170.9	AP ~ *elev* + *PCA* + *wooded* + *fish*	5.58	0.04
5	171.7	AP ~ *PCA* + *wooded* + *substrate* + *fish*	6.36	0.02
6	171.8	AP ~ *PCA* + *wooded* + *fish* + *downed wood*	6.47	0.02
7	172.0	AP ~ *hydro* + *PCA* + *wooded* + *cobble*	6.67	0.02
8	172.0	AP ~ *PCA* + *wooded* + *fish* + *side habitat*	6.70	0.02
9	172.4	AP ~ *hydro* + *PCA* + *emergent* + *wooded*	7.11	0.02
10	172.5	AP ~ *elev* + *hydro* + *PCA* + *wooded*	7.21	0.02
11	173.8	AP ~ *hydro* + *PCA* + *wooded* + *downed wood*	8.51	0.01

Figure 3.4.5 Scaled and centered model-averaged parameter coefficient estimates for the variables included in the set of models holding 95% of the weight of support based on Akaike weights.

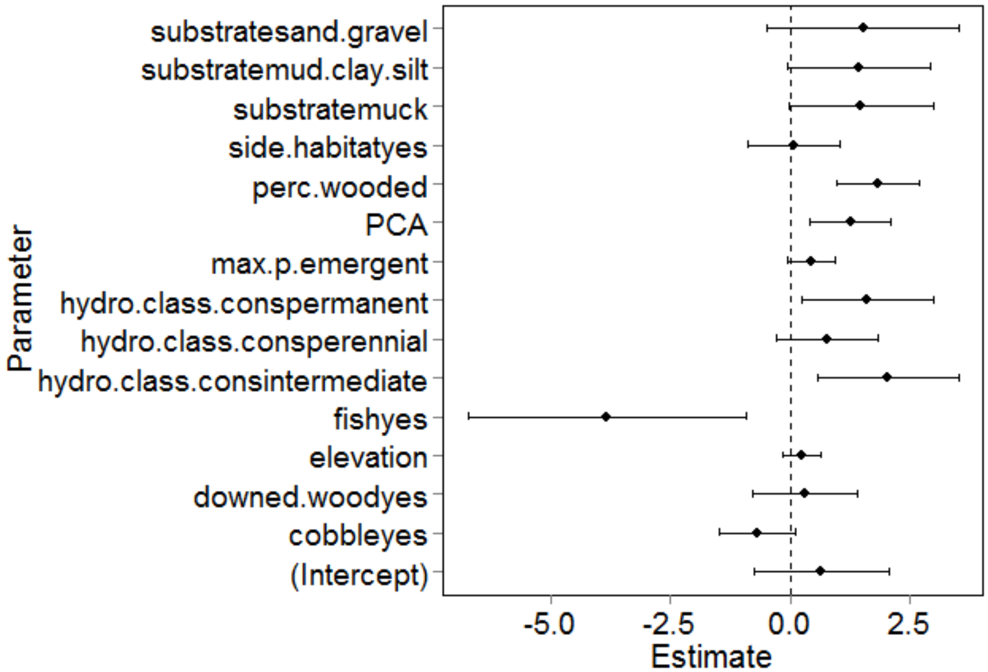


Table 3.4.4 Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels. Variable codes are defined in Table 1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
Intercept	0.65 (-0.76, 2.06)	0.720
elevation	0.23 (-0.17, 0.64)	0.207
*PCA**	1.26 (0.42, 2.10)	0.429
emergent	0.44 (-0.04, 0.92)	0.246
cobble(yes)	-0.69 (-1.48, 0.10)	0.404
*wooded**	1.82 (0.96, 2.68)	0.438
*fish(yes)**	-3.83 (-6.73, -0.93)	1.480
*hydro(intermediate)**	2.04 (0.57, 3.51)	0.750
hydro(perennial)	0.76 (-0.29, 1.82)	0.538
*hydro(permanent)**	1.60 (0.22, 2.99)	0.705
side habitat(yes)	0.07 (-0.87, 1.03)	0.487
downed wood(yes)	0.31 (-0.79, 1.41)	0.562
substrate(muck)	1.48 (-0.02, 2.98)	0.767
substrate(mud.clay.silt)	1.43 (-0.07, 2.92)	0.765
substrate(sand.gravel)	1.51 (-0.47, 3.51)	1.017

Ambystoma macrodactylum (Long-toed salamander): breeding evidence

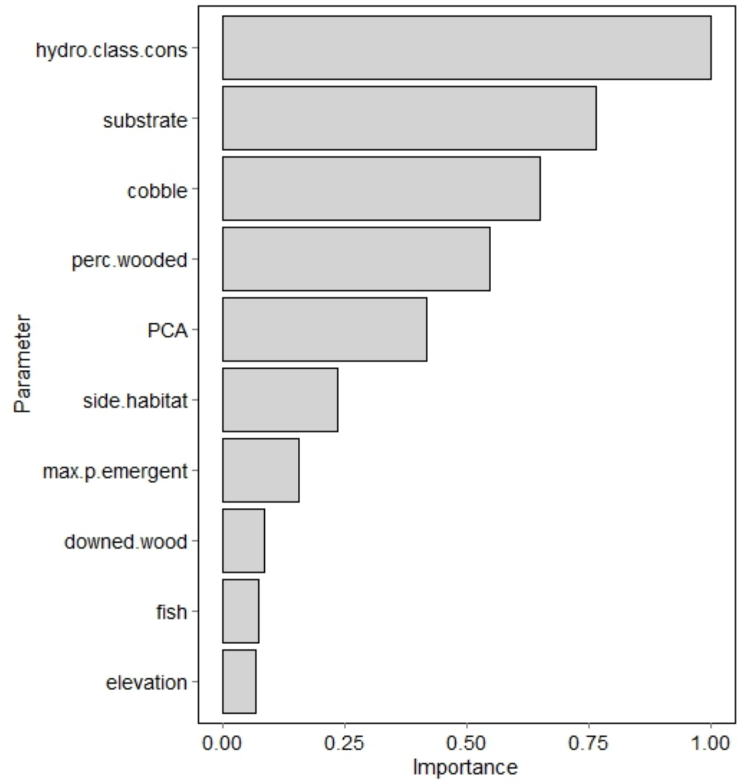
For long-toed salamander breeding evidence, AIC model selection produced a set of 47 models that held 95% of the weight from the candidate set of 210 models. No top model was supported (ΔAIC_{max} = 8.59; maximum w_{Ak} = 0.21; Table 3.4.5) and included hydroperiod class, the percent of wooded perimeter, substrate, and the presence of cobble as having the highest variable importance (Figure 3.4.6). Of these, all but substrate had significant parameter coefficient estimates (Figure 3.4.7 and Table 3.4.6), showing stronger evidence of breeding in intermediate and perennial hydroperiod sites with less wooded perimeter and cobble present. While not significant, the PCA coefficient aligns with hydroperiod observations in a trend towards occupying shallower, smaller sites.

Ambystoma macrodactylum eggs (top) and larva approaching metamorphosis (bottom)

Table 3.4.5 Top ranked models with ΔAIC_c < 4 for *Ambystoma macrodactylum* breeding evidence (BE). *hydro* = hydroperiod, *wooded* = percent of pond perimeter occupied by woods, *PCA* = first axis of PCA, *emergent* = maximum percent of pond occupied by emergent vegetation, *substrate* = pond bottom substrate, *cobble* = presence of cobbles in the substrate, *side habitat* = presence of complex inlet or adjacent wetland habitat. For full set of top 47 models holding 95% of all model support, see Appendix D.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	181.1	BE ~ *hydro* + *wooded* + *substrate* + *cobble*	0	0.21
2	181.5	BE ~ *hydro* + *PCA* + *substrate* + *cobble*	0.44	0.17
3	183.7	BE ~ *hydro* + *wooded* + *substrate* + *side habitat*	2.62	0.06
4	184.0	BE ~ *hydro* + *emergent* + *wooded* + *substrate*	2.91	0.05
5	184.1	BE ~ *hydro* + *PCA* + *wooded* + *substrate*	3.01	0.05
6	184.7	BE ~ *hydro* + *PCA* + *cobble* + *side habitat*	3.62	0.03
7	184.8	BE ~ *hydro* + *wooded* + *cobble* + *side habitat*	3.74	0.03
8	184.8	BE ~ *hydro* + *substrate* + *cobble* + *side habitat*	3.75	0.03

Figure 3.4.6 Relative ranking of variable importance for parameters included in the set of models holding 95% of the weight of support based on Akaike weights for *Ambystoma macrodactylum* adult presence. Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.



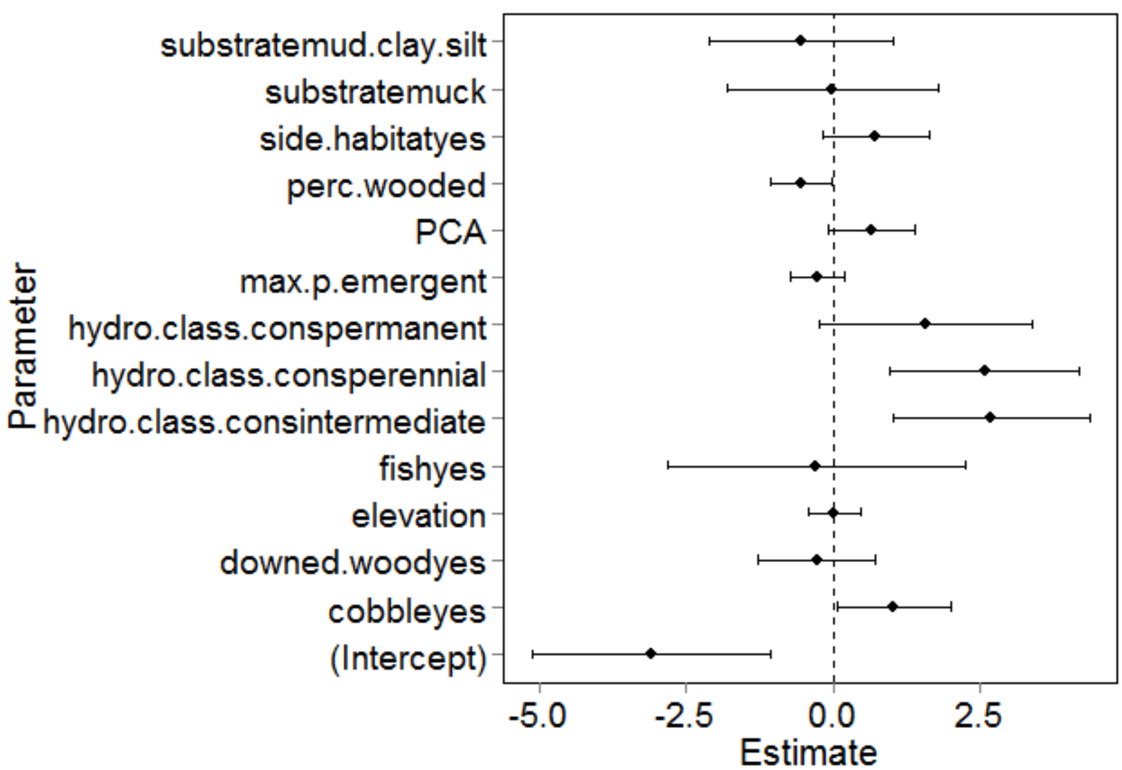


Figure 3.4.7 Model-averaged parameter coefficient estimates for variables included in the set of models holding 95% weight of support based on Akaike weights for *A. macrodactylum* breeding.

Table 3.4.6 Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels for *A. macrodactylum* breeding. Variable codes are defined in Table 1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
*Intercept**	-3.09 (-3.10, -1.06)	1.035
elevation	0.01 (-0.43, 0.46)	0.229
PCA	0.65 (-0.08, 1.39)	0.374
emergent	-0.27 (-0.73, 0.19)	0.235
*cobble(yes)**	1.03 (0.07, 2.00)	0.491
*wooded**	-0.53 (-1.06, -0.01)	0.270
fish(yes)	-0.28 (-2.80, 2.24)	1.284
*hydro(intermediate)**	2.69 (1.01, 4.36)	0.853
*hydro(perennial)**	2.57 (0.96, 4.18)	0.821
hydro(permanent)	1.58 (-0.24, 3.40)	0.927
side habitat(yes)	0.72 (-0.19, 1.63)	0.462
downed wood(yes)	-0.28 (-1.28, 0.72)	0.512
substrate(muck)	-0.01 (-1.81, 1.79)	0.918
substrate(mud.clay.silt)	-0.53 (-2.09, 1.02)	0.795
substrate(sand.gravel)	-17.41 (-2540.03, 2505.20)	1287.070

Ambystoma macrodactylum (Long-toed salamander): adult presence

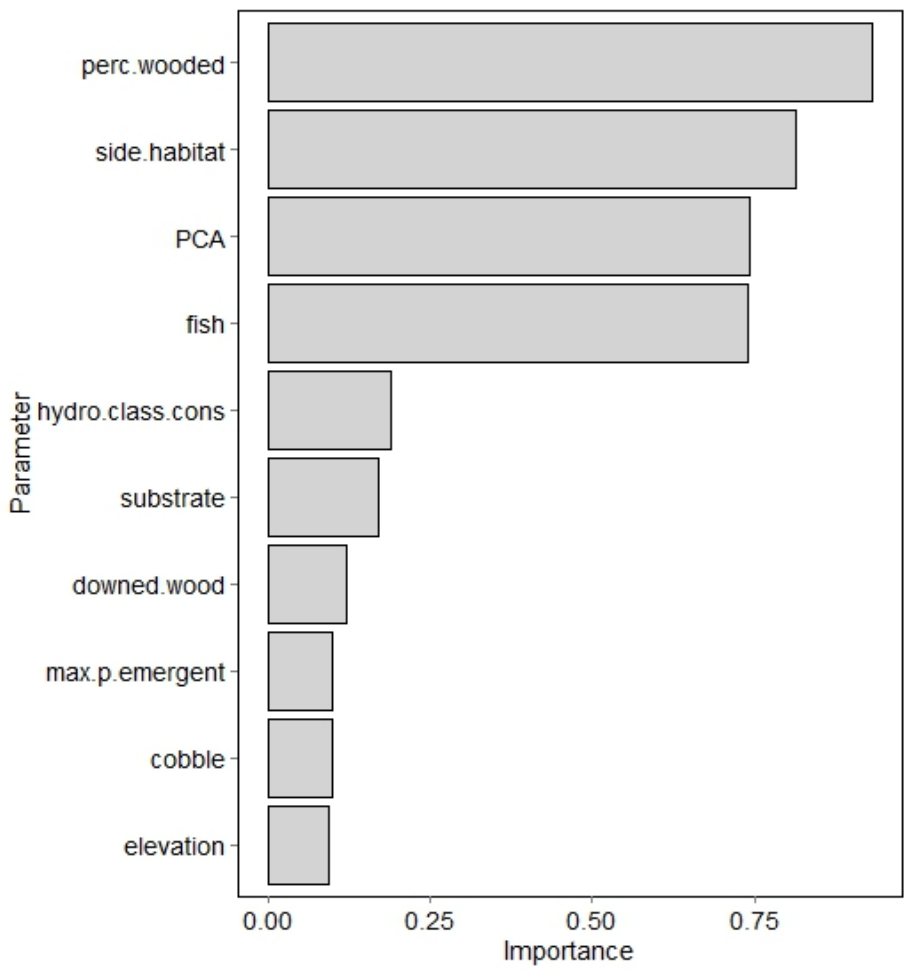
For long-toed salamander adult presence, AIC model selection produced a set of 42 models that held 95% of the weight from the candidate set of 210 models. The top model was moderately supported (ΔAIC_c for second-ranked model = 3.15; ΔAIC_{max} = 10.00; top model maximum w_{Ak} = 0.37; Table 3.4.7) and included pond shape (PCA axis), the percent of wooded perimeter, fish presence, and side habitat having the highest variable importance (Figure 3.4.8). Of these, all but fish had significant parameter coefficient estimates (Figure 3.4.9 and Table 3.4.8), showing stronger association of *A. macrodactylum* adults with bigger, deeper ponds with less shallows, less side habitat, and more wooded perimeter. Fish presence was barely not significant, with a strongly negatively trend in response to fish presence.

Ambystoma macrodacylum adults hiding in ledges in the pond bank (top) and adult underwater in an alpine pond (bottom)

Table 3.4.7 Top ranked models with $\Delta AIC_c < 4$ for presence of *Ambystoma macrodactylum* adults. AP = adult presence, *PCA* = first axis of PCA, *hydro* = hydroperiod, *wooded* = percent of pond perimeter occupied by woods, *fish* = fish presence, *side habitat* = presence of complex inlet or adjacent wetland habitat,. For full set of top 42 models holding 95% of all model support, see Appendix D.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	146.4	AP ~ *PCA* + *wooded* + *fish* + *side habitat*	0	0.37
2	149.5	AP ~ *hydro* + *wooded* + *fish* + *side habitat*	3.15	0.08
3	150.3	AP ~ *PCA* + *wooded* + *substrate* + *fish*	3.93	0.05

Figure 3.4.7 Relative ranking of variable importance for parameters included in the set of models holding 95% of the weight of support based on Akaike weights for *A. macrodactylum* adult presence. Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.



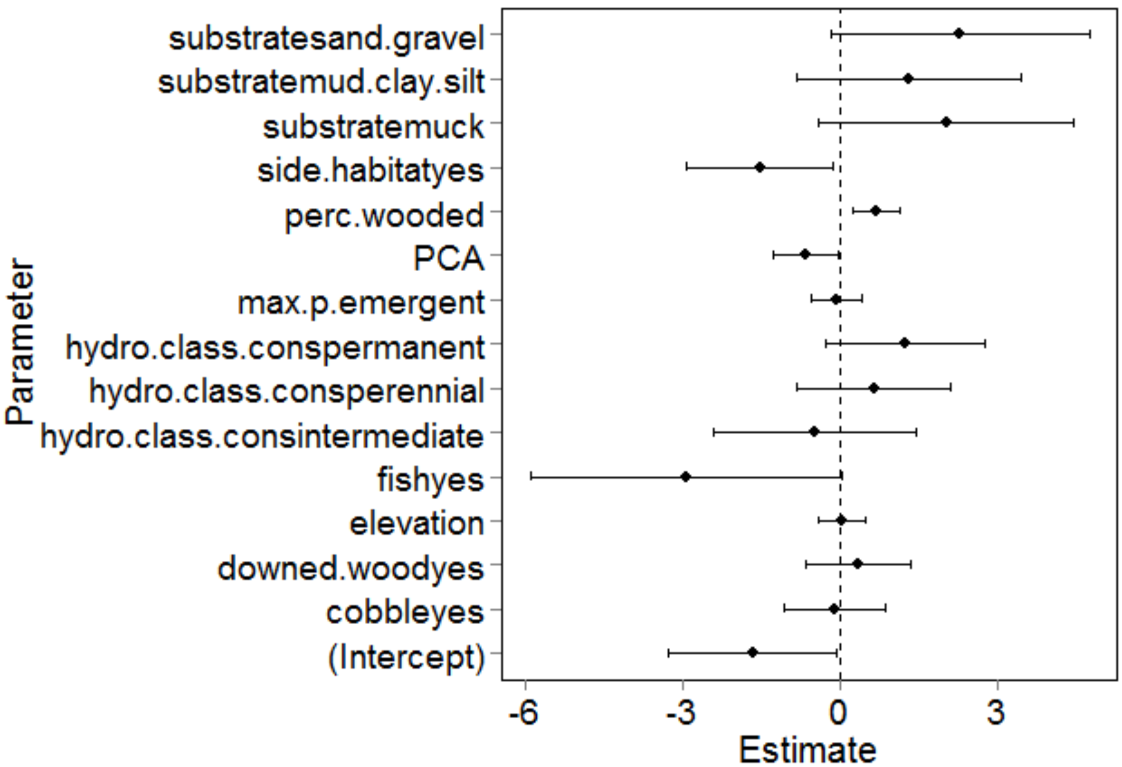


Figure 3.4.8 Model-averaged parameter coefficient estimates for variables included in the set of models holding 95% weight of support based on Akaike weights for *A. macrodactylum* adults.

Table 3.4.8 Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels for *A. macrodactylum* adults. Variable codes are defined in Table 1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
Intercept	-1.65 (-3.26, -0.05)	0.818
elevation	0.05 (-0.39, 0.50)	0.227
*PCA**	-0.64 (-1.26, -0.02)	0.318
emergent	-0.05 (-0.53, 0.43)	0.245
cobble(yes)	-0.10 (-1.07, 0.87)	0.496
*wooded**	0.68 (0.23, 1.14)	0.232
fish(yes)	-2.93 (-5.90, 0.03)	1.512
hydro(intermediate)	-0.49 (-2.42, 1.44)	0.985
hydro(perennial)	0.64 (-0.81, 2.10)	0.745
hydro(permanent)	1.25 (-0.27, 2.76)	0.774
*side habitat(yes)**	-1.52 (-2.91, -0.13)	0.708
downed wood(yes)	0.36 (-0.64, 1.35)	0.506
substrate(muck)	2.02 (-0.40, 4.46)	1.240
substrate(mud.clay.silt)	1.32 (-0.81, 3.44)	1.082
substrate(sand.gravel)	2.29 (-0.17, 4.75)	1.257

Ambystoma gracile (Northwestern salamander): breeding evidence

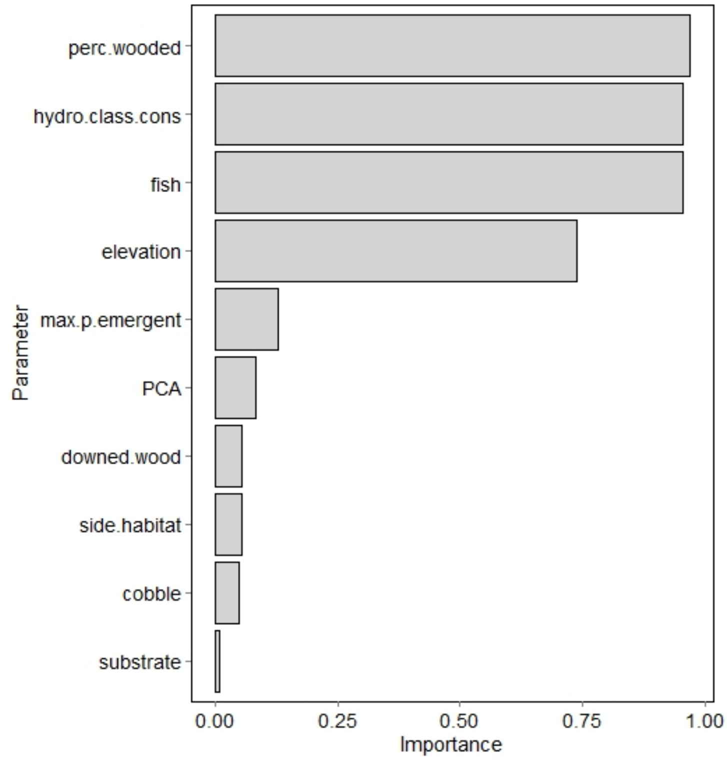
For northwestern salamander breeding evidence, AIC model selection produced a set of 24 models that held 95% of the weight from the candidate set of 210 models. The top model was fairly strongly supported: ΔAIC_c for second-ranking model = 4.42; ΔAIC_{max} = 10.90; maximum w_{Ak} = 0.63; Table 3.4.9). The top model included elevation, hydroperiod class, the percent of wooded perimeter, and fish presence (Table 3.4.9). Percent wooded, hydroperiod class, fish, and elevation had the highest variable importance (Figure 3.4.10). Of these, parameter coefficient estimates were significant for percent wooded, fish, and elevation (Figure 3.4.11 and Table 3.4.10), showing stronger evidence of breeding in lower-elevation sites with more wooded perimeter, and a negative relationship with fish. Data for hydroperiod class were highly skewed, creating statistical problems (e.g. standard errors >2000). Coefficient estimates are reported in the tables, but the relevant parameters are not included in Figure 3.4.11. However the pattern is clear from the raw data: 0/29 ephemeral hydroperiod sites and only 3/25 intermediate sites had signs of *A. gracile* breeding, whereas 11/42 perennial sites and 18/41 permanent sites had breeding activity, indicating a strong association with longer-hydroperiod classes of wetlands.

Ambystoma gracile eggmass attached to a stick (top) and larva (bottom)

Table 3.4.9 Top ranked models with $\Delta AIC_c < 4$ for *Ambystoma gracile* breeding evidence. BE = breeding evidence, *elev* = elevation, *hydro* = hydroperiod, *wooded* = percent of pond perimeter occupied by woods, *emergent* = maximum percent of pond occupied by emergent vegetation, *fish* = fish presence. For full set of top 24 models holding 95% of all model support, see Appendix D.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	141.1	BE ~ *elev* + *hydro* + *wooded* + *fish*	0	0.63
2	145.5	BE ~ *hydro* + *emergent* + *wooded* + *fish*	4.42	0.07

Figure 3.4.9 Relative ranking of variable importance for parameters included in the set of models holding 95% of the weight of support based on Akaike weights for *A. gracile* breeding evidence. Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.



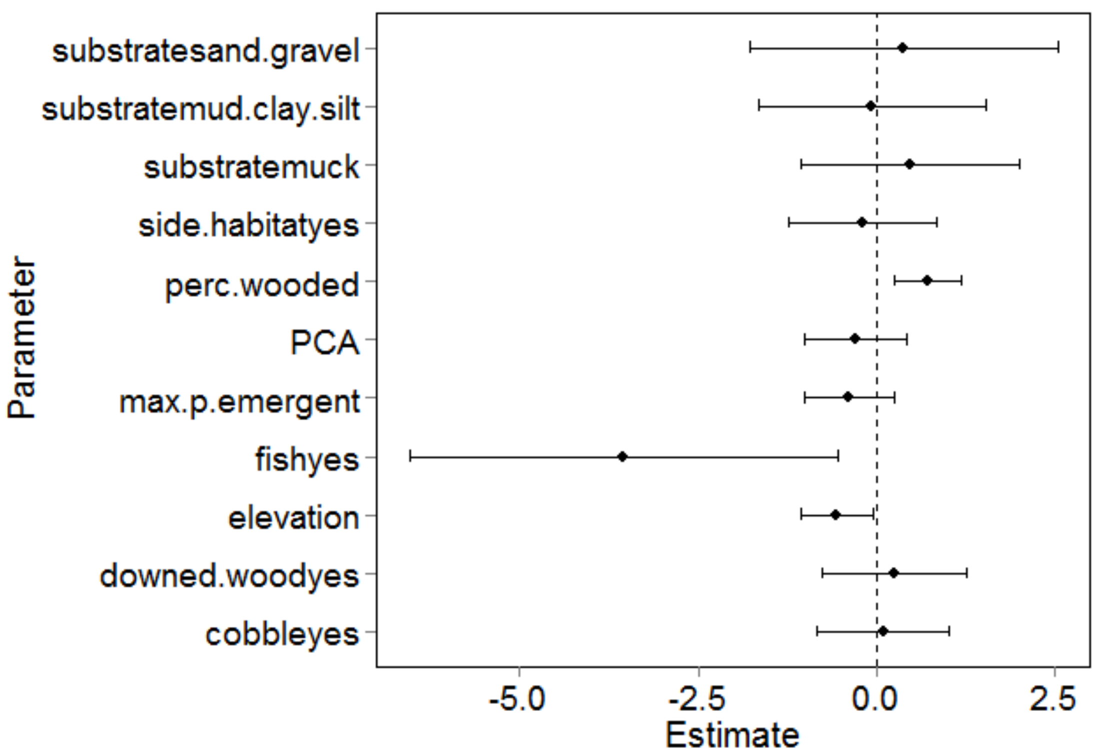


Figure 3.4.10 Model-averaged parameter coefficient estimates for the variables included in the set of models holding 95% of the weight of support based on Akaike weights for *A. gracile* breeding evidence. Hydrologic class is missing from the plot due to the scale of SE.

Table 3.4.10 Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels. Variable codes are defined in Table 1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
Intercept	-17.69 (-2226.82, 2191.44)	1127.130
*elevation**	-0.56 (-1.06, -0.06)	0.256
PCA	-0.30 (-1.01, 0.41)	0.362
emergent	-0.39 (-1.02, 0.24)	0.320
cobble(yes)	0.09 (-0.83, 1.01)	0.471
*wooded**	0.72 (0.25, 1.19)	0.240
*fish(yes)**	-3.55 (-6.54, -0.55)	1.528
hydro(intermediate)	16.57 (-2252.29, 2285.44)	1157.607
hydro(perennial)	17.10 (-2251.77, 2285.97)	1157.607
hydro(permanent)	17.78 (-2251.09, 2286.65)	1157.607
side habitat(yes)	-0.20 (-1.23, 0.85)	0.533
downed wood(yes)	0.25 (-0.75, 1.26)	0.514
substrate(muck)	0.47 (-1.05, 2.00)	0.780
substrate(mud.clay.silt)	-0.06 (-1.66, 1.53)	0.813
substrate(sand.gravel)	0.38 (-1.78, 2.54)	1.100

Ambystoma gracile (Northwestern salamander): adult presence

For northwestern salamander adult presence, AIC model selection produced a set of 18 models that held 95% of the weight from the candidate set of 210 models. The top model was moderately supported: ΔAIC_c for the second-ranked model = 2.79; ΔAIC_{max} = 7.17, maximum w_{Ak} = 0.39; Table 3.4.11). The top model included the percent of wooded perimeter, hydroperiod class, fish presence, and the presence of side habitat as having the highest variable importance (Figure 3.4.12). Of these, all had significant parameter coefficient estimates except hydroperiod class, due to the same statistical issues regarding data skew as for *A. gracile* breeding evidence (Figure 3.4.13 and Table

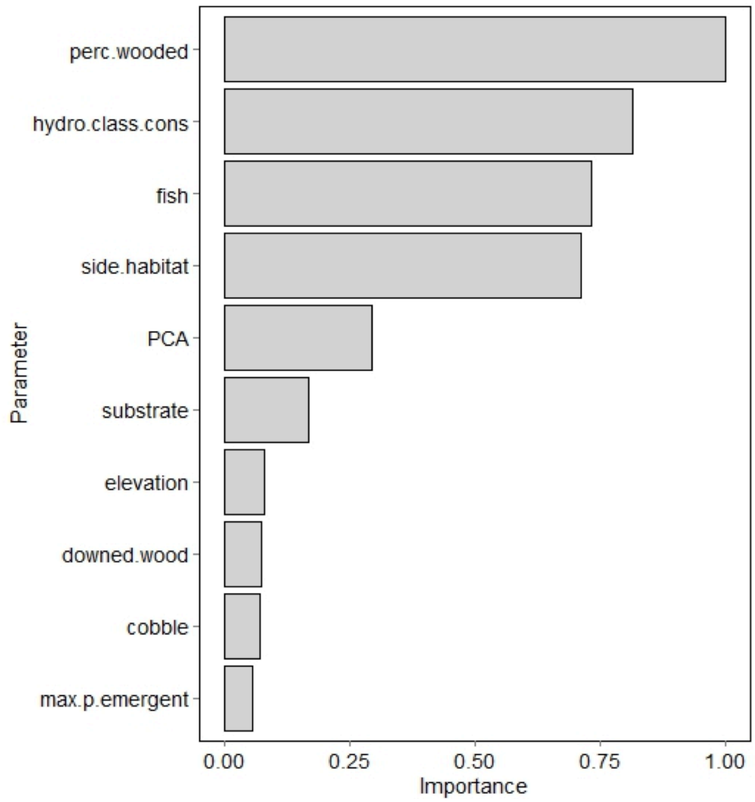
Ambystoma gracile paedomorph (aquatic adult, top) and terrestrial adult (bottom)

3.4.12). Adult *gracile* were associated with ponds with less side habitat and more wooded perimeter, and were negatively associated with fish. As with breeding evidence, adult *A. gracile* predominantly used longer-hydroperiod sites: zero adults were detected in ephemeral ponds, 1/27 intermediate ponds had adults whereas adult *A. gracile* were found in 9/44 perennial and 16/43 permanent ponds. Note that in the case of *A. gracile*, "adults" refer to both terrestrial morphs and paedomorphs, which are the mature aquatic adult form.

Table 3.4.11 Top ranked models for the set of models holding 95% of all model support. *BE* = breeding evidence, *elev* = elevation, *hydro* = hydroperiod, *shallow* = maximum percent shallows, *wood* = percent of pond perimeter occupied by woods, *emergent* = maximum percent of pond occupied by emergent vegetation, *size* = maximum size of the pond during the breeding season, *cobble* = presence of cobbles in the substrate, *side* = presence of side habitat.

Rank	AIC	Model	ΔAICc	w_{Ak}
1	113.5	AP ~ *hydro* + *wooded* + *fish* + *side habitat*	0	0.39
2	116.3	AP ~ *PCA* + *wooded* + *substrate* + *fish*	2.79	0.10
3	117.1	AP ~ *hydro* + *PCA* + *wooded* + *fish*	3.56	0.07
4	117.6	AP ~ *PCA* + *wooded* + *fish* + *side habitat*	4.02	0.05
5	117.6	AP ~ *hydro* + *wooded* + *substrate* + *side habitat*	4.11	0.05
6	117.8	AP ~ *elev* + *hydro* + *wooded* + *side habitat*	4.25	0.05
7	117.9	AP ~ *hydro* + *wooded* + *side habitat* + *downed wood*	4.36	0.04
8	117.9	AP ~ *hydro* + *wooded* + *cobble* + *side habitat*	4.36	0.04
9	118.0	AP ~ *hydro* + *PCA* + *wooded* + *side habitat*	4.43	0.04
10	118.0	AP ~ *hydro* + *emergent* + *wooded* + *side habitat*	4.50	0.04
11	119.3	AP ~ *hydro* + *wooded* + *substrate* + *fish*	5.81	0.02
12	119.4	AP ~ *elev* + *hydro* + *wooded* + *fish*	5.83	0.02
13	119.9	AP ~ *hydro* + *wooded* + *fish* + *downed wood*	6.41	0.02
14	120.0	AP ~ *hydro* + *emergent* + *wooded* + *fish*	6.42	0.02
15	120.0	AP ~ *hydro* + *wooded* + *cobble* + *fish*	6.46	0.02
16	120.1	AP ~ *PCA* + *wooded* + *fish* + *downed wood*	6.52	0.01
17	120.5	AP ~ *PCA* + *wooded* + *cobble* + *fish*	6.92	0.01
18	120.7	AP ~ *elev* + *PCA* + *wooded* + *fish*	7.17	0.01

Figure 3.4.11 Relative ranking of variable importance for parameters included in the set of models holding 95% weight of support based on Akaike weights for *A. gracile* adult presence (terrestrial morphs and paedomorphs). Importance computed by summing Akaike weights (Σw_{Ak}) for every model in which each variable was present.



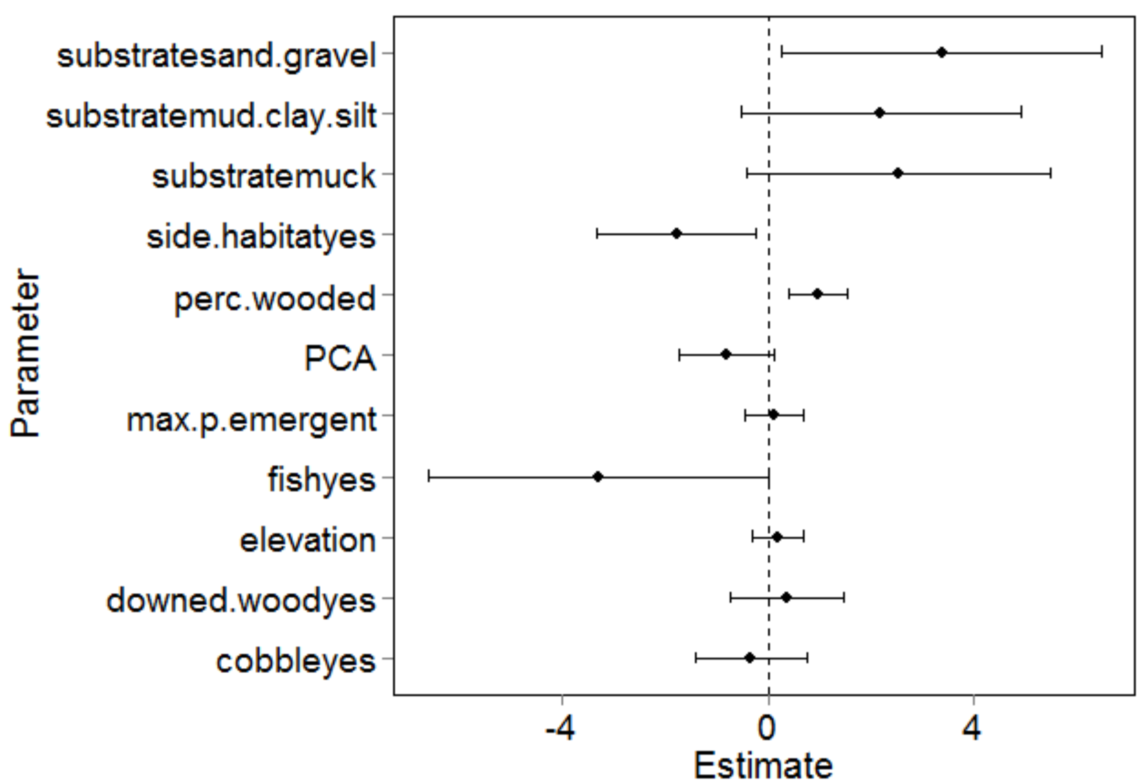


Figure 3.4.12 Model-averaged parameter coefficient estimates for variables included in the set of models holding 95% of the weight of support based on Akaike weights for *A. gracile* adults.

Table 3.4.12 Model averaged coefficients and 95% confidence intervals for factors predicting injury at the individual and habitat unit levels for *A. gracile* adult presence. Variable codes are defined in Table 1. Stars indicate variables with confidence intervals that do not bound 0.

Variable	Model-Averaged Estimate (95% CI)	Unconditional SE
Intercept	-15.96 (-2715.92, 2683.99)	1377.55
elevation	0.18 (-0.32, 0.70)	0.26
PCA	-0.81 (-1.74, 0.13)	0.48
emergent	0.13 (-0.43, 0.71)	0.29
cobble(yes)	-0.32 (-1.40, 0.75)	0.55
*wooded**	0.99 (0.42, 1.55)	0.29
*fish(yes)**	-3.31 (-6.64, 0.02)	1.70
hydro(intermediate)	15.89 (-3007.37, 3039.15)	1542.51
hydro(perennial)	17.61 (-3005.65, 3040.87)	1542.51
hydro(permanent)	18.24 (-3005.02, 3041.49)	1542.51
*side habitat(yes)**	-1.78 (-3.33, -0.24)	0.79
downed wood(yes)	0.37 (-0.74, 1.48)	0.57
substrate(muck)	2.54 (-0.42, 5.51)	1.51
substrate(mud.clay.silt)	2.21 (-0.51, 4.93)	1.39
*substrate(sand.gravel)**	3.39 (0.28, 6.51)	1.59

3.5 Synthesis
Montane Wetlands

Assessment of amphibian vulnerability to future climate change
Sensitivity: Both aquatic life stages (eggs and tadpoles) and adult *Rana cascadae* (Cascades frog) were associated with intermediate hydroperiod ponds, which are also the most sensitive class of wetlands to climate change. *Ambystoma macrodactylum* breeding is associated with intermediate and perennial hydroperiod wetlands, both of which are anticipated to experience reduced water levels and in some cases conversion to shorter-hydroperiod ponds. For this species, which requires multiple years at higher elevations for successful metamorphosis, an increase in the frequency of pond drying, as is projected for these kinds of sites, will have a negative effect on recruitment. Adults in contrast are more strongly associated with deeper, less shallow ponds that are less sensitive to climate impacts. *Ambystoma gracile* appear to be the least sensitive of the three species to climate change, since their breeding and adult habitat use are skewed towards longer hydroperiod permanent ponds. While they also use more climate-vulnerable perennial ponds, they do not rely strongly on the most sensitive wetland types, the intermediate and ephemeral ponds, as either breeding or adult habitat.

Exposure: Exposure varies across the three parks with significant variation in the increase in the likelihood of drying (e.g. for intermediate ponds) across different regions of the parks. Parks also differ in the underlying distribution of pond types across the landscape (Figures 3.5.1-3). In assessing the distribution of sites, it is important to note that our perennial wetland class does not align well with any of the NWI categories, so perennial ponds are likely under-represented in this assessment. Also, as the results of mapping study in Mount Rainier National Park show (Section 3.1), small wetlands of any hydrologic type are substantially underrepresented by the NWI in the montane regions we have studied. Therefore it is fair to assume that we are underestimating the total amount of small wetland habitat, which is of course our primary interest for two species, and also the most at-risk wetland type. We discuss approaches to dealing with this deficiency below. In the meantime, acknowledging the limitations, Figures 3.5.1-3.5.3 and Tables 3.5.1-3.5.3 show the distribution of NWI mapped wetlands overlaid with the VIC model projections for the change in probability of drying for intermediate ponds. Since we cannot parameterize analogous projections for perennial ponds (due to no history of drying in the historical record), we use this projection to also indicate relative risk to perennial ponds assuming that the mechanisms affecting both are the same. Our findings from our focal sites project that 22% of current perennial ponds will become intermediate wetlands by the 2080s, and 3% will become ephemeral. (In contrast, 58% of intermediate wetlands are projected to become ephemeral.) These estimates can be applied to the list below to estimate the shift from perennial to other pond types within each VIC cell (colored grid cell).

In Mount Rainier National Park, our projections suggest that the areas of highest climate

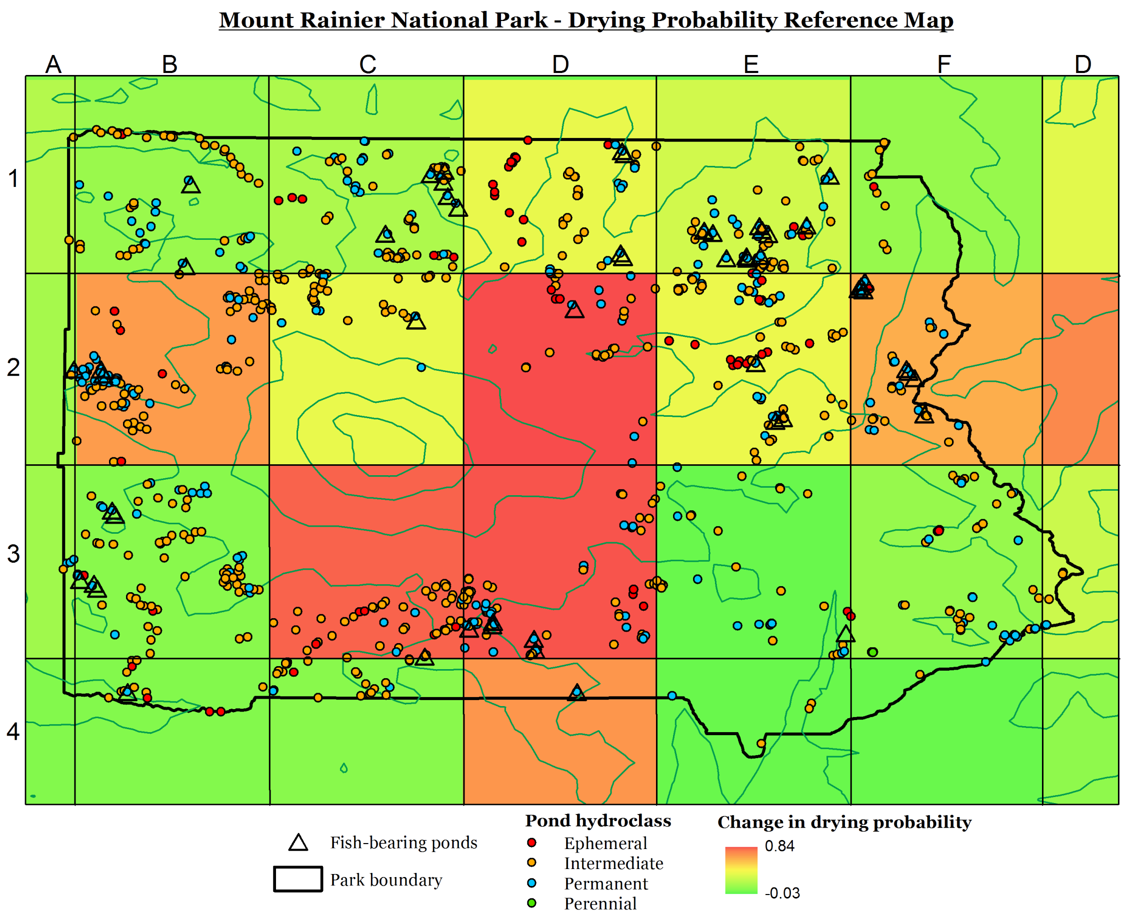


Figure 3.5.1 Mount Rainier National Park wetland and amphibian vulnerability reference map. Colored squares represent VIC grid cells and their projected proportion of change in drying probability for intermediate wetlands. The axis letters and numbers are referenced in Table 3.5.1.

Table 3.5.1. Drying probability reference map for Mount Rainier National Park

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
A1	0.98	0.19	0	2	0	0	2	0
A2	0.99	0.15	0	2	0	2	4	1
A3	0.99	0.12	0	1	0	3	4	0
A4	1	0.05	0	0	0	0	0	0
B1	0.99	0.11	2	32	0	15	49	2
B2	0.99	0.68	4	52	0	35	91	3
B3	1	0.06	4	55	0	20	79	5
B4	1	0.05	4	9	0	1	14	1
C1	0.99	0.17	5	32	0	24	61	7
C2	0.35	0.85	0	30	0	6	36	1
C3	0.82	0.32	5	37	0	5	47	0
C4	1	0.06	2	17	0	5	24	1
D1	1	0.36	13	19	0	10	42	4
D2	0.98	0.85	4	19	0	8	31	1
D3	1	0.83	3	43	0	28	74	5
D4	1	0.7	0	0	0	1	1	1
E1	1	0.28	2	32	0	23	57	14
E2	1	0.37	15	35	0	20	70	3
E3	1	0	1	20	0	11	32	1
E4	1	0	0	3	0	1	4	0
F1	1	0.1	1	8	0	0	9	0
F2	1	0.63	1	14	0	19	34	8
F3	1	0.1	3	28	1	16	48	0
F4	1	0	0	1	0	1	2	0
G3	1	0.25	0	5	0	1	6	0
		TOTALS	69	496	1*	255	821	58

* Note that perennial ponds do not map well to NWI wetland classes, so are underrepresented in our assessment.

impacts that overlap with large numbers of intermediate and perennial ponds are in the central southern part of the Park, with additional areas of significantly elevated climate risk in the east and west (Figure 3.5.1). In North Cascades National Park, the regions of greatest change in the probability of pond drying due to climate change occur in a somewhat patchy pattern across the western half of the park, and with stronger climate impacts generally projected for the west side of the Cascades crest, with exceptions. North Cascades has relatively few mapped wetlands, many of which are permanent so less subject to the kinds of climate impacts we are considering. Many of the clusters of intermediate ponds in the southern part of the Park appear to be at lower risk of climate impacts, while those in the far northern and western regions of the Park are more at risk. Olympic National Park by contrast has many mapped wetlands, a large proportion of which are intermediate wetlands. The areas of greatest change in wetland drying probability are

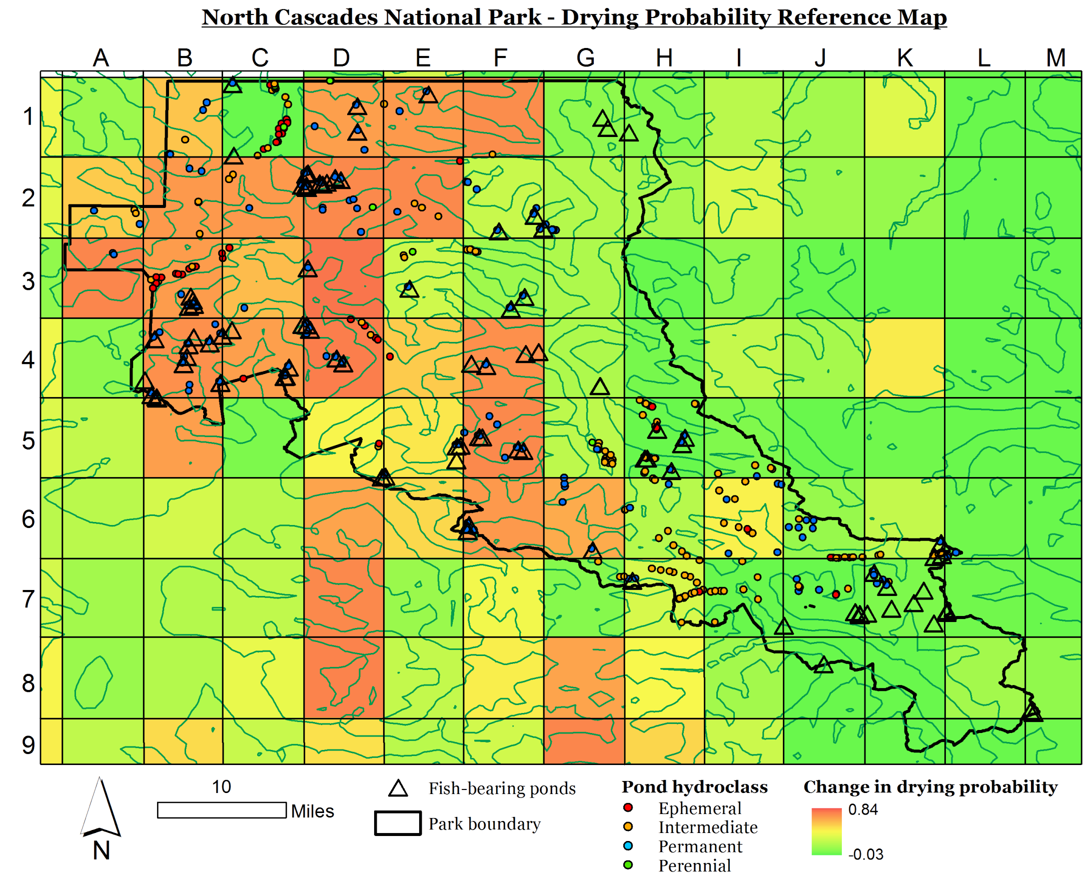


Figure 3.5.2 North Cascades National Park wetland and amphibian vulnerability reference map. Colored squares represent VIC grid cells and their projected proportion of change in drying probability for intermediate wetlands. The axis letters and numbers are referenced in Table 3.5.1.

Table 3.5.2. Drying probability reference map for North Cascades National Park

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
A2	0.55	0.54	0	2	0	2	4	0
A3	0.82	0.74	0	0	0	2	2	0
A4	1	0.09	0	0	0	0	0	0
B1	0.97	0.55	0	1	0	5	6	0
B2	0.83	0.68	0	2	0	3	5	0
B3	0.85	0.68	11	4	0	4	19	4
B4	0.98	0.71	0	0	0	13	13	11
B5	0.94	0.67	0	0	0	0	0	1
C1	1	0	10	10	2	1	23	2
C2	0.84	0.69	0	2	0	2	4	1
C3	0.93	0.59	1	0	0	1	2	0
C4	0.99	0.67	1	0	0	3	4	5
C5	0.99	0.04	0	0	0	0	0	0

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
D2	0.94	0.73	0	0	1	15	16	10
D3	0.78	0.78	0	0	0	1	1	1
D4	0.98	0.76	4	2	0	6	12	4
D5	1	0.41	1	1	0	0	2	0
D6	0.95	0.65	0	0	0	0	0	1
E1	0.68	0.68	0	1	0	2	3	1
E2	0.73	0.73	1	3	0	1	5	0
E3	0.98	0.27	0	2	1	1	4	1
E4	0.99	0.54	1	0	0	0	1	0
E5	0.98	0.46	0	0	0	3	3	4
E6	0.93	0.49	0	0	0	0	0	0
F1	0.89	0.72	0	1	0	0	1	0
F2	0.99	0.25	0	2	0	7	9	3
F3	0.99	0.12	0	5	1	3	9	2
F4	0.93	0.72	0	0	0	1	1	4
F5	0.87	0.73	0	0	0	8	8	4
F6	0.95	0.69	0	0	0	5	5	2
G1	1	0.08	0	0	0	0	0	2
G2	1	0.19	0	0	0	6	6	0
G3	1	0.17	0	0	0	0	0	0
G4	1	0.17	0	0	0	0	0	2
G5	1	0.22	0	12	1	4	17	0
G6	1	0.63	0	0	0	4	4	1
G7	1	0.05	0	2	0	0	2	0
H1	1	0.07	0	0	0	0	0	1
H2	1	0.15	0	0	0	0	0	0
H3	1	0	0	0	0	0	0	0
H4	1	0.02	0	0	0	0	0	0
H5	1	0	4	17	1	3	25	6
H6	1	0.19	0	8	0	3	11	0
H7	1	0.3	2	17	0	2	21	1
I5	1	0.04	0	4	0	1	5	0
I6	1	0.43	1	7	0	5	13	0
I7	1	0	0	9	0	0	9	1
I8	1	0.13	0	0	0	0	0	0
J5	1	0	0	0	0	0	0	0
J6	1	0.1	1	4	0	6	11	0
J7	1	0	3	6	0	4	13	3
J8	1	0	0	0	0	0	0	1
K6	1	0.23	0	6	0	2	8	3
K7	1	0.03	0	2	0	5	7	7
K8	1	0	0	0	0	0	0	0
K9	1	0	0	0	0	0	0	0
L6	1	0.01	0	1	0	2	3	0
L7	1	0.01	0	0	0	0	0	2
L8	1	0.13	0	0	0	0	0	0
L9	1	0	0	0	0	0	0	0
M8	1	0.09	0	0	0	0	0	2
		TOTALS	41	134	8*	140	323	95

* Note that perennial ponds do not map well to NWI wetland classes, so are underrepresented in our assessment.

projected to be the central and western regions of Olympic National Park (Figure 3.5.3), which include some areas (such as along river valleys) with large numbers of intermediate wetlands. Some of these regions are at elevations too low to be occupied by Cascades frogs, for example, but are likely to be used by *Ambystoma macrodactylum*, which can be found at elevations extending down to sea level (though the developmental constraints are less severe as they can metamorphose faster in warmer, lower elevation regions). Of greatest concern for our purposes in this study are the mid to high-elevation regions, primarily within the central part of the Park, where large numbers of intermediate wetlands overlap with elevated drying risk. Table 3.5.3 shows the distribution of these sites in tabulated form.

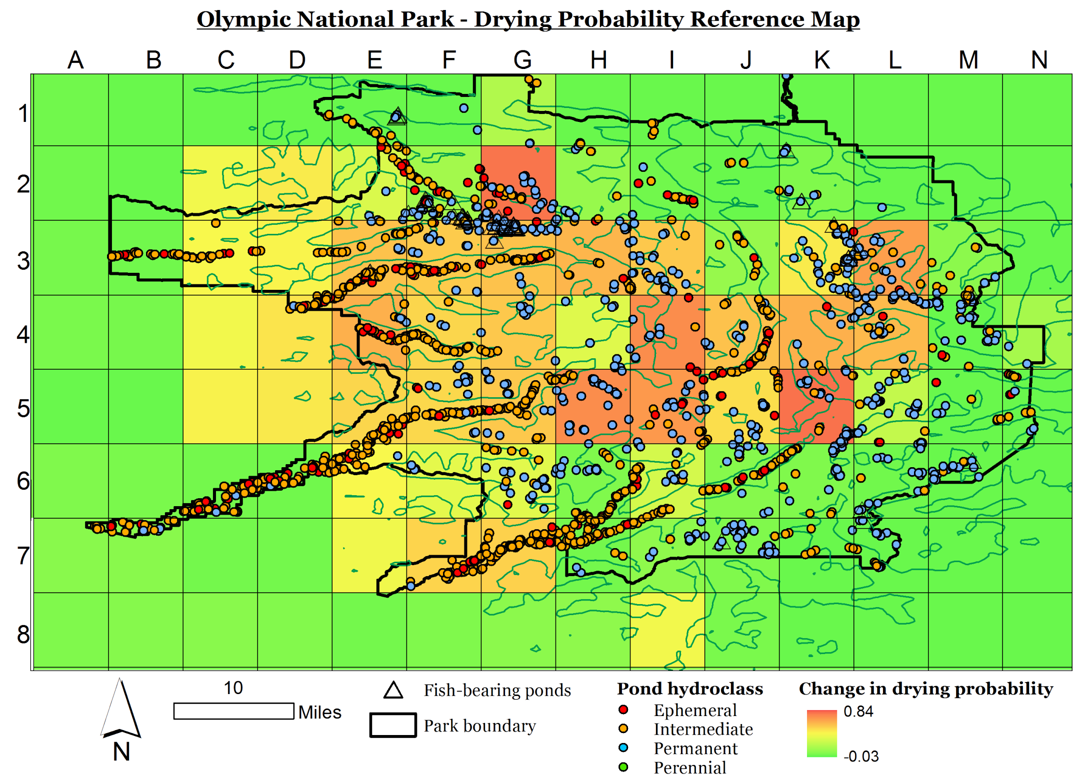


Figure 3.5.3. Olympic National Park wetland and amphibian vulnerability reference map. Colored squares represent VIC grid cells and their projected proportion of change in drying probability for intermediate wetlands. The axis letters and numbers are referenced in Table 3.5.1.

Table 3.5.3. Drying probability reference map for Olympic National Park

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
A7	1.00	0.06	1	4	0	0	5	0
B2	1.00	0.00	0	0	0	0	0	0
B3	1.00	0.01	4	20	0	0	24	0
B6	1.00	0.03	0	0	0	0	0	0
B7	1.00	0.06	4	15	0	4	23	0
C2	1.00	0.39	0	0	0	0	0	0

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
C6	1.00	0.02	10	37	1	3	51	0
D1	1.00	0.00	0	2	0	0	2	0
D2	0.93	0.44	0	0	0	0	0	0
D3	0.89	0.42	0	5	0	0	5	0
D4	0.86	0.46	4	21	0	1	26	0
D5	0.86	0.45	0	0	0	0	0	0
D6	1.00	0.01	13	27	0	1	41	0
E1	1.00	0.00	0	10	0	2	12	6
E2	1.00	0.35	5	7	0	5	17	0
E3	0.94	0.57	7	44	0	6	57	3
E4	0.87	0.61	8	25	0	3	36	0
E5	0.90	0.51	8	30	0	0	38	0
E6	0.90	0.40	0	0	0	3	3	0
E7	0.92	0.38	6	25	0	7	38	0
E8	1.00	0.02	0	0	0	0	0	0
F1	1.00	0.00	0	0	0	2	2	0
F2	0.99	0.13	9	24	0	17	50	26
F3	0.90	0.53	9	24	0	21	54	2
F4	0.84	0.51	1	29	0	6	36	0
F5	0.88	0.50	4	33	0	13	50	0
F6	0.93	0.34	0	0	0	3	3	0
F7	0.84	0.51	6	25	0	7	38	0
G1	1.00	0.18	0	2	0	2	4	0
G2	0.95	0.78	8	12	0	21	41	1
G3	0.94	0.56	10	14	0	39	63	19
G4	0.83	0.55	0	5	0	7	12	0
G5	0.90	0.54	2	34	0	13	49	0
G6	1.00	0.33	1	8	0	18	27	0
G7	1.00	0.52	9	48	0	0	57	0
H1	1.00	0.00	0	2	0	0	2	0
H2	1.00	0.10	0	3	0	11	14	0
H3	0.98	0.59	2	9	0	9	20	0
H4	0.32	0.32	8	25	0	3	36	0
H5	0.83	0.72	0	8	0	23	31	0
H6	1.00	0.04	3	27	0	20	50	1
H7	1.00	0.02	5	47	0	4	56	0
I1	1.00	0.00	0	4	0	0	4	0
I2	1.00	0.01	5	11	0	2	18	0
I3	1.00	0.55	1	6	0	24	31	0
I4	0.92	0.72	2	1	0	9	12	0
I5	0.88	0.68	5	7	0	16	28	0
I6	1.00	0.23	4	24	0	11	39	0
I7	1.00	0.08	0	5	0	10	15	0
J1	1.00	0.00	0	0	0	0	0	0

Cell	2080 Drying Probability	Δ Drying Probability	Ephemeral	Intermediate	Perennial	Permanent	Total	Fish Ponds
J2	1.00	0.00	0	4	0	0	4	0
J3	1.00	0.10	1	9	0	0	10	0
J4	0.95	0.57	8	27	0	9	44	0
J5	0.96	0.48	0	6	0	24	30	0
J6	1.00	0.05	7	14	0	11	32	0
J7	1.00	0.04	0	8	0	1	9	1
K1	1.00	0.00	0	0	0	1	1	0
K2	1.00	0.04	0	3	0	6	9	3
K3	1.00	0.44	0	9	0	28	37	4
K4	0.98	0.61	1	1	0	5	7	0
K5	0.99	0.78	0	6	0	24	30	0
K6	1.00	0.04	1	12	0	18	31	0
K7	1.00	0.00	0	8	0	1	9	0
L2	1.00	0.00	0	0	0	1	1	0
L3	1.00	0.67	2	6	0	13	21	4
L4	1.00	0.59	1	5	0	28	34	0
L5	1.00	0.78	2	5	0	28	35	0
L6	1.00	0.04	0	2	0	19	21	1
L7	1.00	0.00	1	6	1	11	19	1
M2	1.00	0.00	0	0	0	0	0	0
M3	1.00	0.06	0	7	0	4	11	0
M4	1.00	0.00	3	9	0	22	34	1
M5	1.00	0.00	1	4	0	4	9	0
M6	1.00	0.00	0	3	0	15	18	1
N3	1.00	0.00	0	0	0	0	0	0
N4	1.00	0.14	0	0	0	2	2	0
N5	1.00	0.00	3	9	0	5	17	0
N6	1.00	0.00	0	0	0	0	0	0
		TOTALS	198	885	2*	626	1711	74

* Note that perennial ponds do not map well to NWI wetland classes, so are underrepresented in our assessment.

Adaptive capacity: We highlight one primary option for management-based climate adaptation, which is the removal of introduced fish that eat amphibians and tend to limit their distributions to shallower and more at-risk ponds and wetlands (Ryan et al. 2014). Fish removals are within the mandate of the National Parks and are already underway in North Cascades National Park and under consideration elsewhere. As a first step, we report on the location and number of ponds with fish, based on National Park Service records, in relation to the distribution of wetland types and increased drying risk (triangles denoted in Figures 3.5.1-3.5.3 and listed in Tables 3.5.1-3.5.3). From a biological standpoint, the degree to which species like *Rana cascadae* and *Ambystoma macrodactylum* may be able to hasten development sufficiently under warmer conditions to compensate for reductions in hydroperiod is an open question, and was not the subject of our research. We discuss what is known on this topic in the discussion below

Columbia Plateau Wetlands
Our intention in this study was to overlay climate projections for Columbia Plateau wetlands with known distributions of focal amphibians such as tiger salamanders in order to make a preliminary assessment of climate risk for this region. Given the variation in performance of the VIC model for Columbia Plateau sites, coupled with limited accessible biological data, we do not have a sufficiently strong basis of information to conduct a meaningful assessment but hope to do so in the future.

4. Analysis and Findings

4.1 Remote-Sensing of Wetlands
Montane Wetlands
The mapping study for Mount Rainier National Park highlights the high errors of omission of small wetlands, many of which represent critical habitat for amphibians, invertebrates, and other species, in the National Wetland Inventory. Our findings highlight the need for LiDAR across broader regions of the Pacific Northwest in order to update wetland maps. Object based image analysis of LiDAR datasets mapped substantially more montane wetlands than either the NWI or the use of object based image analysis without the use of LiDAR data. Through the use of LiDAR intensity imagery and hydrologic flow modeling of the LiDAR derived digital terrain model we were able to map wetlands that were not detected through visual assessment. Although our secondary analysis exploring remote sensing variables to predict hydrology did not produce conclusive results, it does show promise given a larger sample size.

Columbia Plateau Wetlands
The new remote-sensing methods developed here make it possible to reconstruct hydrologic dynamics of wetlands (Halabisky *et al*., 2013b). This is a fundamental advance, given that the key limiting factor in much wetland science, and in particular assessment of climate impacts and change over time (wetland loss, gain, structural change, etc) is the lack of data on historical wetland dynamics. These methods and the datasets they generate can be used in a large number of ways ranging from research applications, to monitoring, to support for on-the-ground decision-making, to higher order policy evaluations.

For example, as we demonstrate here, reconstructed hydrologic datasets provide important validation datasets for retrospective modeling studies, which make it possible to calibrate models of future climate impacts. Classification of wetland habitat based on seasonal wetland hydrology captured through remote sensing can also be used for a very broad range of conservation, restoration, climate adaptation, and other management applications such as identification of species habitat, landscape vulnerability assessments, and quantification of ecosystem function and services (e.g. water storage capability, carbon and other nutrient fluxes, and pollution filtration to name a few). They can also be used at local and regional scales to locate wetlands undergoing abnormal change. Together with climate data this gives land managers a detailed characterization of wetland stressors useful for targeting conservation and restoration efforts. Finally, at regional and broader scales these methods can be used to enable evaluation of policy objectives such as No Net Loss.

4.2. Monitoring of Focal Field Sites

One of the key limiting factors in wetland science is that lack of data. The empirical datasets developed during this project support not only the analyses done here, but also serve as a repository of information to support future studies.

4. 3 Climate-Hydrologic Modeling

The methods developed here represent a substantial advance in our capacity to model climate impacts to wetlands. Most wetlands models are highly data-intensive yet are implemented for single wetlands. In a few cases, local wetland dynamics have been interpolated across broader regions to explore potential climate impacts (Johnson et al. 2005, 2010). Our work represents the first application of a macroscale model to address climate impacts on wetlands in particular across broad geographic regions. The VIC's capacity to generate projections at two scales – the individual pond and the region – underlies its strength as a modeling tool to support research and management.

Montane Wetlands

In general, our models successfully captured historical wetland dynamics during the ecologically important summer drawdown seasons for four different wetland types. However, the regression models were not as robust in capturing different behavior in different years, highlighting the need for longer (>5 year) datasets. Additionally, datasets with higher within-year resolution would strengthen the regression approach and enable us to better understand both sources of model error (e.g. geology and soil types, topography, distance from weather stations, etc) as well as the uncertainty in the range of potential climate impacts and the hydrologic drivers that underlie impacts on wetlands. Nonetheless, these models, are an important first step in understanding wetland response to climate, and strongly suggest that, looking forward, climate change will significantly alter water availability for individual wetlands, and will lead to substantial future shifts in the distribution and composition of wetlands across montane landscapes of the Pacific Northwest.

Historical model performance

Soil moisture in the bottom soil layer was the best predictor of wetland drawdown for most of the sites investigated, supporting the hypothesis that wetland drawdown cycles are frequently associated with relatively slow drainage and evapotranspiration processes. The regression models demonstrated generally good performance across all four types of montane wetlands within years, successfully capturing the general time series behavior of each wetland. However, regression models performed better in some years than others and simulations were not able to capture all observed variability (e.g. overestimated wetland minimum water level during 2006 in the Deschutes National Forest site, the error in drawdown timing in the Trinity-Alps in 2003, and the missed drawdown timing and/or minimum water levels in Olympic National Park in 2012). These spatial and temporal variations in model performance are expected, and are seen in other comparisons between simulated and observed data at fine spatial scales, such as snow water equivalent measured at individual snow courses (Mote *et al*., 2005). One reason for the discrepancy is that local precipitation is often imperfectly captured in the driving data sets for the

VIC model at high elevations (e.g. data from meteorological stations at lower elevations are interpolated to higher elevations in landscapes with high orographic variation). The estimated uncertainty using multiple years of observations in the Oregon and California sites confirmed that our approach is fairly robust in some regions and/or years. However, at times uncertainties are broad enough to be biologically meaningful (e.g. in terms of evaluating risk to particular species). Likewise, the failure of the regression models to effectively capture strongly different patterns of wetland response to across very different weather years in Olympic National Park shows that this approach is not universally robust. Additional water-level data would help better evaluate the performance of the models, and likely also improve their performance.

Climate impacts on wetlands

Our climate-change projections demonstrate that all four of the wetland types on which we focused (ephemeral, intermediate, perennial, and permanent wetlands) are likely to experience hydrologic changes in response to future climate. However, the intensity and duration of climate change effects will differ markedly among the four types. These changes are also likely to lead to transitions along the continuum of wetland types captured in our hydrologic classes. Specifically, some ephemeral wetlands may essentially disappear and more than half of currently ecologically productive intermediate montane wetlands are projected to become ephemeral wetlands by the 2080s, as more rapid recession rate and earlier drawdown causes wetlands to reach their bottom volume earlier, resulting in more frequent and longer dry seasons in summer. For some perennial wetlands (e.g. Washington sites), transitions from perennial to intermediate wetlands or even to ephemeral wetlands are also projected as wetland water levels drop under climate change. Driving these changes is the fact that most montane wetlands are located either in snow-dominated watersheds or mixed-rain-and-snow watersheds where snowmelt is a key water source in late spring and summer. Because a warmer climate is likely to cause less snow accumulation in winter and earlier snowmelt in spring, montane wetlands are particularly susceptible to climate change, especially in combination with projected drier summers (Hamlet *et al.*, 2013; Elsner *et al.*, 2010).

Comparison between wetlands in Washington and those in Oregon and California also shows that wetlands with seemingly similar hydrologic characteristics are likely to have different sensitivity to climate change depending on local conditions. For example, perennial wetlands in our focal sites in Willamette and Deschutes National Forests, Oregon are likely to be less sensitive to climate change in terms of minimum water level compared to those in Washington. For perennial wetlands in Oregon, simulated summer soil moisture in the VIC simulations was close to residual values nearly every year but the wetlands did not dry out (maintaining ~20 % of their maximum depth) under the current climate. This behavior suggests that these wetlands are coupled to more extensive deep groundwater sources, not captured in the VIC simulations, than wetlands in Washington. For the climate-change scenarios, wetlands in Oregon and California are projected to have earlier drawdown and reach their minimum water level earlier, but without drying out. This supports the argument that wetlands connected to deeper groundwater sources are less vulnerable to increased frequency of drying when compared to surface water-fed wetlands (Johnson *et al*., 2009). However, because the VIC model does not include a deep groundwater component, more sophisticated modeling approaches (such as the use of fine scale groundwater models) may be required to fully capture these effects (Wenger *et al.*, 2010; Safeeq *et al.,* 2014).

Water temperature modeling
Our models were able to generally reproduce historical patterns of wetland temperature dynamics, so suggest that this approach could be expanded to evaluate water temperature impacts of climate change in more detail. Based on our 18 wetlands, our projections show a general increase (average ~2˚C) in the maximum water temperature for all sites in response to increased air temperatures associated with climate change. For permanent wetlands that are generally deeper than other wetland types, observed water temperature showed much less fluctuation on a daily time step (i.e. less sensitive to air temperature) than that of other wetland types. As a result, permanent wetlands showed lower goodness of fit values than other wetland types. Our small sample set of permanent wetlands suggests that elevation may influence sensitivity of water temperatures in permanent ponds to climate change, as would be anticipated based on other research on elevational gradients in hydrologic impacts of climate change. The extent to which the average ~2˚C increase in water temperature will affect the biota and function of sites is likely to be species-specific. These kinds of projections could support research on these impacts by providing a range of plausible temperature effects based on climate projections.

Puget Lowlands Wetlands
Models based on a small number of exploratory sites in one region of the Puget lowlands suggest that climate impacts on lower elevation wetlands on the west side of the Cascades may be less severe than impacts at higher elevations. While a broader base of research (more wetland types, across a broader range of low-elevation regions) is needed to test these conclusions, our findings align with the notion that aquatic systems at middle and higher elevations are likely to be more influenced by climate change due to shifts in snowpack. Snowpack is much less of a factor in lower-elevation watersheds that are already rain-dominated, where patterns of precipitation and associated water flows are projected to shift less dramatically than at higher-elevation sites (Hamlet et al. 2005, Mote et al. 2005).

Columbia Plateau Wetlands
Historical model performance
The VIC model was able to reasonably reproduce historical patterns of wetland dynamics in roughly one third of the wetlands studied, and unable to do so in the rest. In the sites where the VIC approach was reasonably successful, this allows us to 1) further assess historical hydrologic patterns, extending the dataset developed through remote sensing to a longer historical time series (92 years instead of 25), and 2) to make some preliminary assessments of climate impacts on those wetlands that appear to be fairly clearly tied to daily or annual patterns of climate variability. Overall, this initial exploration also highlights the value of these tools for generating more nuanced research questions to explore that will help us better understand the drivers of wetland dynamics. Our initial division of our focal sites into four groups, based on description of their hydrologic behavior in relation to climate, allows us to begin to parse the many kinds of influences that are likely affecting wetlands in the Columbia Plateau in order to further explore them in a more mechanistic framework.

For example, Group 1 wetlands clearly track the high frequency variability associated with seasonal climate variability, which VIC reproduces. This suggests that, for this group of wetlands, there is some physical basis in terms of soil characteristics or other features that create stronger connections to groundwater sources, which in turn determine wetland behaviors mechanistically captured by the VIC model. A clear next step with these wetlands then is to further explore their association with soil, landscape, and other local features likely to affect hydrology, and to investigate how these may differ from other wetlands that do not fit well with VIC simulations.

Both Groups 1 and 2 in some cases exhibited decadal as well as daily and annual patterns of variation – i.e. multi-year periods of unusually high or low water levels that appear in both the reconstructed remotely sensed datasets and model simulations (though sometimes only in the annually-based models). The fact that for Group 1 sites fitting the VIC soil moistures model, the cool season precipitation model was a roughly equivalent fit is not surprising, since soil moisture dynamics are an integrator of cool season precipitation. In essence they are equally good predictors. However, for Group 2 sites observed variability was beyond that captured by simulated soil moisture dynamics on which the daily-based regression model was developed. In that case, the annually-based cool season precipitation model was a substantially better fit than the daily-based multivariate regression model. For Group 2 wetlands, it is hard to say that climate is the major driver of wetland dynamics (e.g. in cases where the variability from VIC is very small compared to the broader wetland pattern of behavior). As with Group 1, an obvious step is to see whether any on-the-ground features are clearly associated with the distinction between Group 1 and 2 (or others) that suggest a mechanistic difference underlying their categorization and behaviors. For example, are the sites that appear to be most sensitive to cool season precipitation potholes where the soil does not transmit water well? These would represent a different kind of reservoir than that modeled by VIC soil moisture, and may be less sensitive overall to temperature variability as a result. Overall what is different about these places?

The key questions that these observations generate relate to the mechanisms underlying hydrologic patterns. In this case we can use the Groups to generate hypotheses. For example, how do more complex wetland dynamics relate to local features? Under which soil, geographic, and other conditions is the VIC model of soil moisture dynamics sufficient to capture wetland dynamics? Overall, in the case of the Columbia Plateau wetlands, there is not a clear geographic signal among wetland types and groups. This suggests that instead something about the microcharacteristics of the wetlands are making them behave differently as opposed to regionally varying factors. Their differences could, for example, relate to a range of local variables including the depth and drainage characteristics of soils, aquifer structure and complexity, underlying geology, or elevation and the possible role of snow.

In summary, our four groups suggest the following lines of exploration. First, in which cases (what kinds of wetlands, landscape features, etc) are hydrologic dynamics driven by climate variability that is captured by the VIC model? Alternatively, in which cases (what kinds of wetlands, landscape features, etc) are dynamics driven primarily by precipitation? For example, which wetlands are closed systems with stream inputs, or what are their connections to groundwater flows or seeps? As more localized information becomes available, our "Groups" may remain intact or may split into further distinctions. The interesting question is where the breakpoint lies in having detailed enough information to adequately model and capture historical dynamics with the VIC while maintaining the benefits of the VIC as a macroscale regional model, and understanding its applications and limits.

One expected limitation of the VIC is in cases of wetlands, such as those proposed for Group 3, which appear to have substantial human influence. In these cases, the lack of fit to the VIC, along with observed patterns in the remotely sensed dataset independently, illuminates questions about 1) what is happening on the ground and 2) whether local knowledge can help discern those patterns. For example, in sites that exhibit anomalous patterns or poor fit to the

VIC model, are there particular hydrologic signatures associated with increased rates of well construction, groundwater mining, diversions, or other human activities?

The limitations of our study in linking patterns to mechanisms highlights the need to better characterize a subset of the actual wetlands to support the next step of analyses. Which of these factors are most important will also determine the degree to which wetlands are likely to shift with climate.

Climate impacts on wetlands

Given the limitations of the VIC simulations in recreating historical hydrologic dynamics in the Columbia Plateau wetlands, climate impacts are a challenge to evaluate overall. One observation is that in general in the Group 1 and 2 wetlands (in which we have more confidence in the models), median water levels do not substantially change. This could mean that wetlands have a better groundwater connection, i.e. this is the reason they exist at all, and also makes them less sensitive to climate impacts. (This assumes that groundwater is less subject to climate impacts, on which there is debate.) Because groundwater flows are not explicitly included in the VIC model, these connections make it hard to characterize groundwater-fed sites with the VIC. However, there may be ways to recognize sites strongly linked to groundwater using the VIC model, based on model behavior or patterns of divergence from VIC predictions, so this is a potential area of future exploration.

Overall, what we seek to understand in terms of modeling climate impacts to wetlands with the VIC model is where we can or cannot ignore certain hydrologic drivers for certain kinds of wetlands. What we are looking for ultimately are classifications that relate to climate change sensitivity. (There is an analog to systems with or without snow in West side (montane and lowlands) sites; knowing where this boundary is determines in large part which wetlands will be much more sensitive to temperature.) One challenge currently in the case of the Columbia Plateau is that all of our variables are correlated with each other, so we do not have an independent predictor of wetland behavior.

4.4 Ecological Modeling

Montane Wetlands

In our study we focused on three pond-breeding amphibians: *Rana cascadae, Ambystoma macrodactylum,* and *Ambystoma gracile.* In the preliminary analyses presented here, across all species either hydroperiod or in one case pond shape (i.e. first PCA axis that differentiated deep, large from shallow, smaller wetlands) was among the highest variable importance in each of the six analyses (each species, analyzed by breeding evidence and adult presence). Either hydroperiod or the pond shape PCA axis was a significant parameter coefficient (with the exception of *A. gracile*, where positive observations were so skewed towards deeper pond types that the statistics failed).

The specific relationships of each species to hydroperiod differed, however. *Rana cascadae* breeding was strongly associated with intermediate and perennial wetlands. This likely reflects the beneficial growth conditions found there (warmer ponds allow faster developmental rates), as long as they do not dry. These sites are also unlikely to be occupied by fish, as discussed below. Adult habitat use for *Rana cascadae* was most strongly associated with intermediate ponds, but was also significantly greater in permanent ponds (compared to ephemeral sites). There was a positive but not significant association with perennial ponds for adults. This split distribution is likely to be capturing multiple uses for these different kinds of sites. For example, early season use of adult *R. cascadae* for breeding, and later summer and fall use of permanent ponds for foraging. *Ambystoma macrodactylum* likewise predominantly used intermediate and perennial ponds for breeding. However adult *A. macrodactylum* were more strongly associated with deeper, less shallow ponds. *Ambystoma gracile* showed a different pattern, with both breeding and adult presence strongly associated with permanent, and to a lesser degree perennial, pond types.

Despite having observations of fish in only 9 out of the 168 sites surveyed, fish also appeared in all of the top models, often with a statistically significant negative effect, and with a negative effect in all cases. These findings – the importance of hydrologically-related features and of fish – support our expectations that these two factors would be of importance for amphibians. Other important factors varied by species and life stage. The common inclusion of the percentage of wooded perimeter in many of the top models may reflect on-the-ground conditions and microclimates in the mountains more accurately than a courser measure like elevation (which also appeared in several top models). Therefore it was not a surprise that species such as *Rana cascadae* and *Ambystoma gracile* were associated with more heavily forested ponds, while *Ambystoma macrodactylum*, known to be the highest elevation species of the three that may be found above treeline, had a negative relationship with forest cover.

One of the questions that may be answered by future occupancy analysis of this dataset is the degree to which our findings may be improved with estimates of detection. Particularly for species such as *A. macrodactylum* that have larvae that are known to be more active at night, and adults that are relatively small and cryptic compared to the other two species, this assessment will be important. We might expect some associations to strengthen based on incorporation of detection rates. For example, *A. macrodactylum* are associated with higher elevation ponds with cobble in the substrate. The same feature (cobble) also acts as refugia in which larvae can hide to avoid detection. Next steps are to further explore these data with specific hypotheses that incorporate interactions among variables, and to investigate the effect of detection probabilities on estimates of occupancy associated with different habitat types.

4.5. Synthesis

Sensitivity: The differences in breeding and adult foraging habitat use and life history requirements among our three focal species translate into different levels of climate-related risk of habitat loss that most clearly could affect breeding and recruitment. *Rana cascadae* is of greatest concern, as a montane obligate species not found at lower elevations, which heavily relies for recruitment on intermediate and perennial ponds that are at highest risk of climate impacts. *Ambystoma macrodactylum* also appear to be at substantial risk of losing breeding habitat due to increased pond drying rates in montane and alpine regions. While in a general sense *A. macrodactylum* is buffered somewhat by its broader range (found from sea level up to alpine regions), the species is doubly at risk of negative climate impacts in montane regions due to 1) its reliance on intermediate and perennial ponds for breeding and 2) its requirement of multiple consecutive years of water for larvae to complete metamorphosis at higher elevations. Therefore while Cascades frogs are likely to be most affected by reduced times to pond drying, risk to long-toed salamanders is amplified by the projected increase in the inter-annual frequency of pond drying. *Ambystoma gracile* appear to be at lowest risk of direct negative impacts on breeding habitat, due to their reliance on longer hydroperiod kinds of ponds that according to our analysis are less sensitive to climate change. However, while *Ambystoma gracile* appear likely to experience less direct habitat loss, shifts in pond conditions or the frequency of drying in perennial sites may have other life history impacts, such as shifting the relative frequency of metamorphosis versus paedomorphosis. This possibility generates additional interesting questions about how survival rates vary in alpine regions among the two adult forms, whether those survival rates may be affected by climate change, and whether shifts in the frequency of adult morphs could have implications for demographic rates and population viability under climate change. Likewise, while our analysis does not address impacts of climate change beyond effects on breeding habitat, we would anticipate a broader range of demographic effects to either exacerbate or help compensate for recruitment losses.

Exposure: Overall, we found considerable and in some cases severe potential impacts of climate change on montane wetlands in all three National Parks, with the magnitude of impacts varying in space across each landscape with factors such as mountain topography and other key drivers of regional climate variation. Our assessment provides a first step in evaluating the exposure of wetlands and montane species to climate change, with more advances needed. Because the wetland distribution presented here is based on the National Wetland Inventory (NWI), cross-walked to our pond classifications, as noted above we are likely under-representing perennial ponds here since this category does not map well to the NWI classifications. Also, as the results of our remote-sensing study and mapping of wetlands in Mount Rainier National Park show (Section 3.1), small wetlands of any hydrologic type are substantially underrepresented by the NWI, at least for the montane regions we have studied. Therefore it is safe to assume that our assessment underestimates the number of small ephemeral, intermediate, and perennial wetlands in our three focal landscapes. The degree to which these errors of omission differ across those landscapes is an open one that we now have the tools to answer were LiDAR coverage, for example, to become available for North Cascades and Olympic National Parks. Nevertheless, the NWI is a good starting point to begin to assess areas of highest risk to amphibians based on the combination of wetland types and the degree of risk associated with climate change. As LiDAR becomes available for North Cascades and Olympic National Parks, the methods used in Mount Rainier may be extended there to develop better estimates.

Adaptive capacity: A promising approach to building resilience in montane wetland ecosystems is the possibility of targeting removal of introduced fish – known to have strong negative effects on a suite on native montane species – to regions where removals could restore habitat that is otherwise not available to amphibians and other native species affected by fish. The dominant effect of fish in our results, despite the very small sample of sites with fish in our surveys (~5%) supports the preponderance of evidence that introduced fish harm native montane ecosystems. Likewise, the demonstrated success of fish removals, and rapid unassisted recolonization by native amphibians and invertebrates shows the real potential of this approach for getting ahead of negative climate impacts (Ryan et al. 2014). The resources provided here can help Park managers and other land managers identify, for example, priority regions where habitat loss and fish presence are projected to most severely interact. Our team is working on further assessment of this as well.

A key area of uncertainty is in the biological capacity of amphibians to respond to climate impacts. Amphibians as a group are highly adapted to variable conditions, but little is known about the plasticity of alpine amphibians in response to climate impacts. For example, for our focal species, there are zero published studies of responses of different life history stages to climate-related impacts. A primary question in terms of breeding success is whether faster tadpole or larval development in ponds with increased water temperatures could compensate for faster pond drying rates. Observations of stranded tadpoles in dried ponds suggest that selective pressure for faster development is there in some years but plasticity is currently insufficient in many cases. For example, 2012 and 2013 were climate analog years in terms of the degree of drying in montane and alpine regions of the Pacific Northwest, and we observed substantial mortality of tadpoles due to pond drying in both years. In wetlands not at risk of drying entirely, ecological effects may also depend on how thermal conditions in ponds change as the climate warms and water levels drop (O'Regan *et al.*, 2013; Ryan *et al.*, 2014; Tarr & Babbitt, 2008). Overall, the potentially complex demographic effects of climate change on different life history stages leaves ample room for research and many uncertainties (Windler and Schindler 2004; Amburgey *et al.,* 2012; Duarte *et al.* 2012; Gerick *et al.* 2014). Therefore proactive management approaches to building resilience (aka adaptive capacity) provide some insurance in the face of those uncertainties.

For amphibians in particular, already known to be in declines in many montane regions, climate impacts are likely to interact with non-climate threats such as disease, pollution, and the presence of introduced fish (Ryan *et al.*, 2014; Adams *et al.*, 2013; Piovia-Scott *et al.*, 2011; Knapp *et al*., 2007; Davidson, 2004). Amphibians and invertebrates are also important prey for many montane species, so population declines in these assemblages could propagate up food webs, negatively affecting the birds, non-avian reptiles, and mammals that rely on them as prey (Epanchin *et al.*, 2010; Polis & Strong, 1996). Overall, species' exposure will depend on what kinds of wetland habitat they use, the current distribution of wetland types across landscapes, and the degree of change in spatial and temporal hydrologic patterns under future climates (Ryan *et al.*, 2014).

Beyond our three focal species, the broad range of ecological roles played by wetlands means that altered hydrology across whole landscapes will reverberate in many ways, ranging from shifts in wildlife habitat to water storage to patterns of nutrient transfer and transformation. Patterns of soil inundation, for example, determine rates of carbon sequestration and release, nitrogen transformations, and other nutrient cycles. Likewise, changes in temporal pulses of peak water affect local pond metabolism and primary productivity, the structure of plant communities, and patterns of wildlife connectivity (Mitsch & Gosselink, 2007). Montane wetlands serve as critical habitat for a wide variety of species, many of which are adapted and sensitive to particular hydrologic regimes that are projected to shift under future climates. Therefore the hydrologic shifts evident in future projections of wetland dynamics imply widespread changes in the many ecological roles served by wetlands.

5. Conclusions and Recommendations

Summary of Major Conclusions

Remote Sensing

- In montane sites, current wetland maps have high errors of omission for small ponds and wetlands in particular. The methods described here substantially improve wetland mapping accuracy (to >90%, up from <65%) and also show promise in capacity to remotely classify pond hydrologic features such as hydroperiod and drying rate.

- In the Columbia Plateau (with direct applications to other semi-arid and arid regions), remote sensing approaches are a game-changing solution to the persistent problem of wetland data deficiency. They can be used to generate retrospective data that is rare, critically needed, and otherwise lost in time. The range of potential applications of these methods and datasets is extremely compelling, including research, management, and conservation, restoration, and policy assessment efforts due to their power in reconstructing historical hydrologic patterns of wetlands variation and change over time, improving statistics, and calibrating models of climate impacts.

Focal Field Studies

- On-the-ground observations remain key to linking sophisticated technological modeling approaches to a core understanding of hydrologic mechanisms and their associated influences on species and ecosystems. This work is time consuming but irreplaceable in the insight it yields and capacity to bridge larger-scale studies to dynamics at local scales.

Climate-hydrologic Modeling

- The methods developed here represent a substantial advance in our capacity to model climate impacts to wetlands. Our work represents the first application of a macroscale model to address climate impacts on wetlands in particular across broad geographic regions. The VIC's capacity to generate projections at two scales – the individual pond and the region – underlies its strength as a modeling tool to support research and management.
- The VIC model shows substantial promise as a means of reconstructing historical hydrologic data, as an extension of the remote sensing methods above, and to model future climate impacts. Our relatively robust results, particularly in montane wetlands, contradict the assumption that wetland dynamics are by definition too complex to model. Overall, the models presented here offer a first step in beginning to fill the gap in scientific resources for wetland conservation, vulnerability assessment, and climate adaptation planning at both local and regional scales.
- The VIC approach works well in some regions and wetland types, and not in others.
- For montane wetlands, our approach demonstrates a promising first step in relating simulated macro-scale hydrologic variables to observed wetland hydrologic behavior, and projecting the impacts of climate variability and change on montane wetlands in Washington, Oregon, and California. This shows that in many cases wetlands only exist in response to the current climate (e.g. ephemeral and many intermediate wetlands), thus if as the climate changes some of these wetlands will be lost or will transition to shorter-hydroperiod types. In montane sites, the primary limitation of the VIC was in capturing interannual variation. This is likely due to data paucity in regions with little historical study of wetlands, and too much cloud cover to apply the remote sensing methods feasible for more arid regions.
- In Columbia Plateau sites, the central challenge is a lack of on-the-ground information to associate VIC patterns with specific hydrologic mechanisms. Unlike montane sites in which we can count on climate being a consistent driver of hydrologic shifts, the climate of the Columbia Plateau is fairly uniform across the region, yet wetlands show a lot of

variability. To understand the hydrology of these sites and how to best apply the VIC model approach, we need further exploration and collaboration to move analyses to the next step that accounts for local and regional variations in features affecting hydrology and the degree of human impacts.

- The value of VIC is that it has a climate variability signal in it, so can point to fact that some wetlands are more or less driven by climate. From these observations, we can develop hypotheses to test further. In this sense, one of the values of the VIC, beyond its capacity to in some cases generate robust historical hindcasts and future projections, is that it generates questions about wetland dynamics to motivate more in-depth studies.
- With remotely sensed datasets now available for some regions, sample size of wetland observations is no longer an issue, and instead the issue is whether VIC models fit or not. This allows us to look in more detail at how models do or do not capture the systems under study, and to examine what are the robust relationships with climate variables.

Ecological Modeling

- Ecological models show that three focal species of amphibians that use montane and alpine ponds and wetlands have differential reliance on the four wetland hydrologic classes, and that these differences relate to their vulnerability to climate impacts.
- At highest risk, based on the sensitivity of their core habitat to climate-induced drying, is the Cascades frog, *Rana cascadae*. However, the Cascades frog's capacity to use a range of pond classes in the absence of fish suggests opportunities for resilience if enough fish-free habitat remains or is made available through management actions.
- Long-toed salamanders, *Ambystoma macrodactylum*, are also at elevated risk of negative effects of climate change on breeding habitat due to their reliance on intermediate and perennial ponds, and additionally their life history requirement of multiple years of consecutive pond inundation to successfully metamorphose in higher elevation environments.
- Northwestern salamanders, *Ambystoma gracile*, are associated with generally less at-risk pond types (perennial and permanent ponds). However, their life history vulnerability, i.e. need for ponds that retain water for multiple consecutive years in order for larvae to complete metamorphosis, means that they will also experience elevated risk in regions with more severe climate impacts and in particular transitions from perennial or permanent to intermediate pond habitats.

Synthesis

- The combination of our four lines of research link observations on the ground that a core assemblage of wetland-reliant species (pond-breeding amphibians) are currently most reliant on the kinds of wetlands that are both a) the most commonly omitted from existing wetland maps and b) the most vulnerable to climate-induced hydrologic changes over the coming decades. Fortunately opportunities do exist to ameliorate impacts through methods with proven success such as fish removals, and these can be applied to existing management plans such as North Cascades High Lakes Fisheries Management Plan.
- Our synthetic approach also suggests that climate-related risk varies considerably across and among the three focal National Parks – Mount Rainier, North Cascades, and Olympic National Parks – thus management efforts and future research and monitoring may be targeted accordingly and applied if desired to an adaptive management framework.

Challenges

Remote Sensing

One of the challenges that remains is scaling up the remote sensing algorithms to map large regions. Because of the high resolution of datasets greater computational power is necessary to process large volumes of data across regions. An additional challenge for mapping and evaluating montane wetlands is the lack of LiDAR data for many regions. LiDAR data would in our case allow us to apply the algorithms developed for mapping wetlands in Mount Rainier to North Cascades and Olympic National Parks, which would allow us address many of the questions raised above. For example, our assessment of the proportion of wetland habitat loss or conversion across all three National Parks is constrained by the knowledge that our current maps are insufficient, especially for the small ponds and wetlands that are our focus. This also affects managers' capacity to accurately target priority regions for fish removal. Finally, a persistent challenge is the lack of field data covering a wide variety of wetland types to test out the ability of remote sensing to map wetlands and their hydrologic regime. These data would be particularly helpful in understanding some of the patterns observed, for example, in our VIC model analyses of the Columbia Plateau.

Field Studies

The central challenge in wetland science is a dearth of historical data and current monitoring. While our methods generate several means of reconstructing historical data, a broader system of wetlands monitoring is sorely needed to be able to develop a more rigorous, scientifically based understanding of wetland dynamics and their ecological implications.

Climate-Hydrologic Modeling

Data limitations again are the key constraint for climate-hydrologic modeling of wetlands. Because our methods in montane regions were applied mostly in wetlands with at most a few years of observed hydrologic data (often only a single year), extending these approaches to confirm the robustness of our approach over different ecoregions, additional wetland types, and across a longer time series are essential next steps. These models also need to be coupled to better on-the-ground or remote sensing-derived data on wetland occurrence and type so that the most useful predictions about historical and/or future wetland changes can be made. In complex regions that include substantial human impacts such as the Columbia Plateau, on-the-ground data on local soil and landscape features and anthropogenic drivers of hydrologic change are essential for understanding patterns derived from remotely sensed datasets and VIC models.

Ecological Modeling & Synthesis

The questionable robustness of our VIC simulations for a majority of Columbia Plateau wetlands, coupled with limited ecological data, meant that we had insufficient data resources to conduct a rigorous preliminary assessment of climate impacts to Columbia Plateau amphibians. We hope to remedy this through the next steps of our research. For the montane assessment, we mention five species in our proposal. Observations of *Taricha granulosa* and *Bufo boreas* were so limited that we were not able to conduct rigorous statistical analyses on these species. We are in the process of further analyzing amphibian data using a variety of additional statistical techniques, including but not limited to occupancy modeling to extend the use of this dataset.

Key Learning & Next Steps

Overall we are happy with the progress made through this grant. In terms of things we would do differently, there were no substantial misfires, but are likely opportunities to augment our datasets and capacity to evaluate them through new collaborations with researchers and managers studying wetlands on the ground. While we have invested substantial time in seeking out these data resources and relationships, we nonetheless hope to further develop them in the future, with regard to both targeted applications of our scientific resources and data through which to improve our ability to interpret our findings (e.g. VIC groups) and tie them to local dynamics on the ground.

Remote Sensing

Key next steps are to extend the remote sensing methods developed here to broader geographic regions and a broader range of wetland types, and to further evolve the tools for remotely classifying wetlands in more complex landscapes such as our montane sites.

Climate-Hydrologic Modeling

Next steps to explore using the VIC approach are described above. Additional next steps are to experiment with other modeling approaches in addition to the VIC, which offer a range of model complexity from microtopography and groundwater interactions to simple regression models. Members of our group are currently developing a range of products that can be projected forward such as simple groundwater models coupled to VIC recharge. In this case, the VIC models evaporation, precipitation, infiltration, etc, which can then be used to as groundwater recharge inputs for a simple groundwater model that produces a steady state groundwater field over a large area. This hybrid approach would overcome some of the limitations of the VIC while also maintaining its capacity to model physically-based wetland dynamics over a much broader geographic region than is possible with more computationally and data-intensive integrated groundwater-surface water (IGWSW) modeling approaches. Alternatively, where IGWSW models are available, VIC could be used to explore which elements of the more sophisticated model are captured by simpler models such as the VIC.

Ecological Modeling & Synthesis

Tying the remote sensing products developed here to ecological data representing a variety of taxonomic groups (e.g. waterfowl, amphibians, invertebrates) is a key next step that would support a broad range of restoration, conservation, and management efforts linking private landowners; state, tribal, and federal land managers; municipal and state water quality, flood control, pollution control, etc efforts; and conservation, restoration, and climate adaptation planning. Additionally, extending the scope of our research to include additional scales of ecological function served by wetlands (such as nutrient fluxes, carbon sequestration, etc) and how these may be affected by climate change would be exciting. Building on our extensive existing datasets, we are also in a position to generate and test hypotheses regarding the metapopulation and metacommunity dynamics of our focal species that would be of interest both to managers concerned with population viability and to questions of basic science.

6. Management Applications and Products

Uses

All of our products (wetland maps, reconstructed and empirical datasets, future climate impacts projections) can be used by managers to evaluate historical changes in wetland hydrology and potential future changes across the range of applications stated above.

Collaborations with Managers and Decision-Makers

We have worked closely throughout this project with managers and scientists with the National Park Service such as Regina Rochefort (North Cascades National Park, Science Advisor), Barbara Samora (Mount Rainier National Park, Research Coordinator), Jerome Freilich (Olympic National Park, Research Coordinator); various members of the North Cascadia Adaptation Partnership; land managers in the Columbia Plateau such as Michael Rule (Turnbull Lakes, Wildlife Biologist), Sonia Hall (The Nature Conservancy, Arid Lands Initiative, Arid Lands Ecologist); Juli Anderson (Swanson Lakes, Manager)

North Cascades National Park is currently using our projections to evaluate their multi-year plan for fish removals as a part of the Park's High Lakes Fisheries Management Plan. We are in discussions with Michael Rule about an application of our modeling approach to management decision making on the Turnbull Lakes Wildlife Refuge. We have also been approached by a broad range of potential partners interested in our work in the Columbia Plateau in particular from groups such as Ducks Unlimited, The Nature Conservancy, Washington Department of Fish and Wildlife, US Bureau of Land Management, Foster Creek Conservation District, Environment Canada, Washington State Wetland Monitoring Group, and others.

Outreach

Over the past two years we have conducted multiple outreach activities including:

- **Pacific Northwest Wetlands Symposium**, November 2012 in Seattle, where we brought together ~40 wetlands researchers, scientists, and managers in collaboration with EcoAdapt to gather feedback on our approaches while they were in development, and stimulate discussion and collaboration on wetlands climate adaptation efforts.
- We hosted a special session titled ***Climate Adaptation & Pacific Northwest Freshwater Wetlands: Strengthening Links between Science and Management*** at the 2014 Pacific Northwest Climate Science Conference in Seattle that included our core team along with agency partners Regina Rochefort and Michael Rule.
- We have also given roughly ten individual presentations at various conferences on this work (Pacific Northwest Climate Science Meeting, International Congress for Conservation Biology, World Congress of Herpetology, International Workshop on the Analysis of Multi-temporal Remote Sensing Images, Society of Wetland Scientists Pacific Northwest Chapter, International Conference on Climate Change: Impacts and Responses)
- We gave two management-oriented webinars, one for the North Pacific Landscape Conservation Cooperative and another for the US Fish and Wildlife Service on this work.
- We published one article describing our synthetic approach applied to montane amphibians in *Frontiers in Ecology and the Environment* (Ryan et al. 2014). We have two other publications currently in review, one focused on climate-hydrologic modeling of montane wetlands (Lee et al. *in review* at PLoS ONE) and one focused on historical

reconstructions of wetland hydrology (Halabisky et al. *in review* at Remote Sensing of Environment). We have three more manuscripts currently in preparation, on methods for mapping montane wetlands using LiDAR (Halabisky et al. *in prep*), a synthesis of our approaches for amphibian vulnerability assessment in Mount Rainier, North Cascades, and Olympic National Parks (Ryan et al. *in prep*), and a synthesis of remote sensing and VIC modeling approaches for the Columbia Plateau (Halabisky et al. *in prep*). Portions of the text above are taken from our manuscripts in preparation.

- We are in frequent contact with a wide range of land managers, fellow academic and government researchers, and conservation groups regarding our work and its applications.

Thanks

We would like to thank the Northwest Climate Science Center for making this work possible, as well as our partnering funders, the North Pacific Landscape Conservation Cooperative, the National Park Service, the David H. Smith Conservation Research Fellows Program, the Precision Forestry Co-op, and The Washington State Conservation Commission. We would also like to thank Regina Rochefort, Barbara Samora, Jerry Freilich, and other partners at the National Park Service for their engagement on the project and assistance with permits; Mike Adams and Lara Hansen for intellectual input and mentorship; the Earth to Ocean Research Group at Simon Fraser University for intellectual input, in particular Robin Munshaw who is co-leading portions of the ecological analyses and Viorel Popescu for statistical advice; Noll Steinweg, Mara Healy, Rae Parks, and Reed McIntyre the fantastic field crew; Chris Vondrasek and Max Sugarman for help with field work and remote sensing analysis.

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Appendix A. OBIA ruleset

Customized Features:

2006-2009: [2006ImageBrightness]-[2009ImageBrightness]

2006ImageBrightness: ([Mean NAIP2006_Red]+[Mean NAIP2006_Green]+[Mean NAIP2006_Blue])/3

2009ImageBrightness: ([Mean NAIP2009_Blue]+[Mean NAIP2009_Green]+[Mean NAIP2009_Infrared]+[Mean NAIP2009_Red])/4

Canopy Height: [Mean hh]-[Mean be]

NDVI: ([Mean NAIP2009_Infrared]-[Mean NAIP2009_Red])/([Mean NAIP2009_Infrared]+[Mean NAIP2009_Red])

NDWI2009: ([Mean NAIP2009_Green]-[Mean NAIP2009_Infrared])/([Mean NAIP2009_Green]+[Mean NAIP2009_Infrared])

Perimeter to Area: [Border length]/[Area]

Redness2006: [Mean NAIP2006_Red]/([Mean NAIP2006_Blue]+[Mean NAIP2006_Green]+[Mean NAIP2006_Red])

Redness2009: [Mean NAIP2009_Red]/([Mean NAIP2009_Blue]+[Mean NAIP2009_Green]+[Mean NAIP2009_Infrared]+[Mean NAIP2009_Red])

Process: Main:

do

Classify Roads, Streams, Canopy - LiDAR

chessboard segmentation: chess board: 1 creating 'New Level'

assign class: unclassified with Mean Slope <= 1e-005 and Area >= 1000 ha at New Level: background

assign class: with Id: Roads = 0 at New Level: Road

merge region: Road at New Level: merge region

assign class: unclassified with Mean Flow >= 2500 at New Level: Stream

grow region: loop: Stream with Canopy Height <= 1.75 at New Level: <- unclassified Mean Intensity_1 <= 55

Classify Ponds - LiDAR

assign class: Stream with Mean Slope <= 3 at New Level: Pond

assign class: Stream with Mean Depth >= 0.1 and Mean Slope <= 4.5 at New Level: Pond

merge region: Pond at New Level: merge region

assign class: Pond with Area <= 15 Pxl at New Level: Stream

merge region: unclassified at New Level: merge region

multiresolution segmentation: unclassified at New Level: 10 [shape:0.1 compct.:0.5]

assign class: unclassified with Canopy Height >= 2.25 at New Level: canopy

merge region: canopy at New Level: merge region

assign class: unclassified with Mean Intensity_1 <= 60 and Mean Slope <= 5 at New Level: Pond

assign class: unclassified with Mean Intensity_1 <= 60 and Mean Depth >= 0.1 at New Level: Pond

merge region: Pond at New Level: merge region

assign class: unclassified with Mean Intensity_1 <= 60 and Mean Slope <= 9 at New Level: PotentialPond
assign class: PotentialPond with Rel. border to Pond >= 0.1 at New Level: Pond
find enclosed by class: canopy, Stream, Water, unclassified at New Level: enclosed by Pond: Pond, Water +
merge region: Pond at New Level: merge region
assign class: 2x: Stream with Rel. border to Pond >= 0.1 at New Level: Pond
merge region: Pond at New Level: merge region
assign class: Pond with Area <= 5 Pxl at New Level: unclassified

Find Ephemeral Wetlands - LiDAR
assign class: unclassified with Mean Depth > 0.1 and Mean Slope <= 5 at New Level: Temporary Wetland
merge region: Temporary Wetland at New Level: merge region
assign class: Temporary Wetland, Water with Area <= 10 Pxl at New Level: unclassified
assign class: Temporary Wetland with Rel. border to Pond > 0.01 at New Level: Pond

Find Ephemeral Wetlands - LiDAR2
assign class: unclassified with Mean Slope <= 3.5 and Max. pixel value CTI >= 14 at New Level: Emergent Wetland
assign class: unclassified with Mean Slope <= 3 and Max. pixel value CTI >= 9.5 at New Level: Emergent Wetland
assign class: unclassified with Mean Slope <= 3.5 and Mean Depth > 0 at New Level: Emergent Wetland
assign class: unclassified with Mean Slope <= 2.5 at New Level: Emergent Wetland
assign class: loop: Emergent Wetland with Rel. border to Emergent Vegetation > 0 at New Level: Emergent Vegetation
merge region: Emergent Vegetation at New Level: merge region
merge region: Emergent Wetland at New Level: merge region
assign class: Emergent Wetland with Area <= 150 m^2 and Mean Slope > 1.5 at New Level: unclassified
assign class: Emergent Wetland with Border to Pond > 1 Pxl at New Level: unclassified

Find Emergent Veg surrounding ponds - LiDAR
merge region: Emergent Wetland, unclassified at New Level: merge region
chessboard segmentation: unclassified at New Level: chess board: 1
assign class: loop: unclassified with Mean Depth > 0.01 and Border to Pond >= 1 Pxl at New Level: Emergent Vegetation
assign class: loop: unclassified with Mean Depth > 0.01 and Border to Emergent Vegetation >= 1 Pxl at New Level: Emergent Vegetation
assign class: loop: unclassified with Mean Slope <= 2 and Border to Pond >= 1 Pxl at New Level: Emergent Vegetation
assign class: loop: unclassified with Mean Slope <= 2 and Border to Emergent Vegetation >= 1 Pxl at New Level: Emergent Vegetation
merge region: Emergent Vegetation at New Level: merge region
assign class: Emergent Vegetation with Rel. border to Pond >= 0.8 at New Level: Pond

Cleanup - LiDAR

assign class: unclassified with Rel. border to Emergent Vegetation >= 0.58 at New Level: Emergent Vegetation
assign class: Emergent Wetland with Distance to Emergent Vegetation <= 50 Pxl at New Level: Emergent Vegetation
assign class: Pond with Rel. border to Stream >= 0.2 and Area <= 50 Pxl at New Level: Stream

Merge Polygons - LiDAR

merge region: Emergent Vegetation at New Level: merge region
merge region: Ephemeral Pond at New Level: merge region
merge region: Pond at New Level: merge region
merge region: Water at New Level: merge region
merge region: Wet Meadow at New Level: merge region
merge region: Temporary Wetland, Wet Meadow at New Level: merge region
merge region: Wetland at New Level: merge region
merge region: Stream at New Level: merge region

Cleanup - LiDAR

assign class: steep, Tree Canopy, Vegetation at New Level: unclassified
assign class: Ponds, Pond with Canopy Height >= 2 at New Level: unclassified
assign class: Emergent Vegetation, PotentialPond, Stream, unclassified with Area <= 6 Pxl and Rel. border to Pond >= 0.1 at New Level: Pond
assign class: 3x: Emergent Vegetation, PotentialPond, Stream, unclassified with Rel. border to Pond >= 0.7 and Rel. border to Pond >= 0.1 at New Level: Pond
assign class: 3x: Emergent Vegetation, Stream, unclassified with Rel. border to Pond >= 0.7 and Rel. border to Pond >= 0.1 at New Level: Pond
assign class: Stream, unclassified with Area <= 10 Pxl and Rel. border to Emergent Vegetation >= 0.1 at New Level: Emergent Vegetation
merge region: Pond at New Level: merge region
merge region: Stream at New Level: merge region
merge region: Emergent Vegetation at New Level: merge region
assign class: PotentialPond with Area <= 20 Pxl at New Level: unclassified
assign class: Pond with Mean Intensity_1 >= 100 and Area <= 50 Pxl at New Level: Temporary Wetland
assign class: Pond with Mean Flow > 40000 at New Level: Stream

Wetland Complex

copy image object level: Emergent Vegetation, Emergent Wetland, Pond, Stream at New Level: copy creating 'complex' above
chessboard segmentation: Emergent Vegetation, Pond, Stream at complex: chess board: 1
assign class: Emergent Vegetation, Emergent Wetland, Pond, Stream with Mean Flow >= 5000 at complex: Stream
assign class: Stream with Border to Stream >= 1 Pxl at complex: complex
merge region: complex at complex: merge region
assign class: Emergent Vegetation, Emergent Wetland, Pond at complex: complex
merge region: complex at complex: merge region
assign class: Stream with Rel. border to complex >= 0.25 at complex: complex
merge region: complex at complex: merge region

Identify Ponded Streams - Complex
assign class: complex with Mean Flow >= 5000 and Area <= 5000 m^2 at complex:
Stream
assign class: Stream with Existence of sub objects Pond (1) > 0 at complex:
PondedStream
assign class: PondedStream with Area > 100 m^2 and Mean Slope > 4 at complex:
Stream
Merge Polygons
do
merge region: loop: Emergent Vegetation at New Level: merge region
merge region: loop: Pond at New Level: merge region
merge region: Stream at New Level: merge region
Grow Ponds - Imagery
chessboard segmentation: Emergent Vegetation, PotentialPond, unclassified at New
Level: chess board: 1
grow region: loop: Pond at New Level: <- Emergent Vegetation 2009ImageBrightness
<= 90
grow region: loop: Pond at New Level: <- Emergent Vegetation 2006ImageBrightness
<= 100
assign class: 4x: with Rel. border to Pond >= 0.3 and NDWI2009 >= 0.5 at New
Level: Pond
merge region: Pond at New Level: merge region
Multi image hydrology
Hydrology
merge region: Pond at New Level: merge region
assign class: 4x: Stream with Rel. border to Pond > 0.25 at New Level: Pond
merge region: Pond at New Level: merge region
merge region: Emergent Vegetation at New Level: merge region
Hydrology during 2009
copy image object level: Pond at New Level: copy creating '2009' below
chessboard segmentation: Pond at 2009: chess board: 1
assign class: Pond with 2009ImageBrightness >= 190 at 2009: 2009_snow
assign class: Pond with Mean NAIP2009_Infrared > 90 at 2009: Dry2009
assign class: Pond with Mean NAIP2009_Infrared > 27 at 2009: Shallow2009
assign class: Pond with Mean NAIP2009_Infrared <= 27 at 2009: Deep2009
assign class: with 2009ImageBrightness >= 190 at 2009: 2009_snow
Hydrology during 2008
copy image object level: Pond at New Level: copy creating '2008' below
chessboard segmentation: Pond, 2008Ponds at 2008: chess board: 1
assign class: Pond with Mean Intensity_1 <= 0 at 2008: zero intensity
assign class: Pond, 2008Ponds with Mean Intensity_1 >= 60 at 2008: Dry2008
assign class: Pond, 2008Ponds with Mean Intensity_1 > 0 at 2008: Shallow2008
Hydrology during 2006
copy image object level: Pond at New Level: copy creating '2006' below
chessboard segmentation: Pond at 2006: chess board: 1
assign class: Pond with Mean NAIP2006_Blue >= 215 at 2006: 2006_snow

```
            assign class: Pond with 2006ImageBrightness >= 125  and 2006ImageBrightness <=
200  at  2006: Dry2006
            assign class: Pond with 2006ImageBrightness >= 100  at  2006: Shallow2006
            assign class: Pond with 2006ImageBrightness < 100  at  2006: Deep2006
      Identify Meadows
         assign class: unclassified with NDVI > 0  at  New Level: meadow
         merge region: loop: meadow at  New Level: merge region
         find enclosed by class: meadow with Area <= 150 m² at  New Level: enclosed by
canopy, meadow: canopy, meadow +
         find enclosed by class: canopy with Area <= 150 m² at  New Level: enclosed by
meadow: meadow +
         merge region: loop: meadow at  New Level: merge region
         merge region: loop: canopy at  New Level: merge region
      Export Preliminary Results
         export vector layers: Emergent Vegetation, PondedStream, Pond, Stream at  New Level:
export object shapes to SprayPonds2014k
         export vector layers: complex, PondedStream2, PondedStream, Stream at  complex:
export object shapes to Spraycomplex_2014k
      Mininum Mapping Unit using imagery
         assign class: Ponds, temp ponds, 2006Ponds, 2009Ponds with Area <= 350 Pxl and
2006-2009 <= -5  at  New Level: unclassified
         assign class: DoqqPonds, Ponds, temp ponds, 2006Ponds, 2009Ponds with Area <= 35
Pxl at  New Level: unclassified
         assign class: Ponds with Area <= 100 Pxl and Mean Slope >= 10  at  New Level: temp
ponds
      Pond Area
         assign class: Deep2006, Shallow2006 at  2006: 2006Ponds
         assign class: Deep2008, Dry2008, Shallow2008, zero intensity at  2008: 2008Ponds
         assign class: 2008Ponds at  2008: Pond
         assign class: Deep2009, Shallow2009 at  2009: 2009Ponds
         export vector layers: Emergent Vegetation, Pond at  New Level: export object shapes to
Spray_pondarea
      temp code
         do
         assign class: Stream with Mean Depth >= 0.1  and Mean Slope <= 2  at  New Level:
Pond
         assign class: Stream with Mean Depth >= 0.34  and Mean Slope <= 7  at  New Level:
Pond
         assign class: Pond with Area <= 0.002 ha at  New Level: Stream
         assign class: Water with Area <= 0.003 ha at  New Level: unclassified
```

Appendix B. Field sites for hydrologic monitoring.

Table B1. List of wetlands monitored for hydrologic change and used in the climate-hydrologic analyses, and their form of monitoring. Under site locations, MORA is Mount Rainier National Park, NOCA is North Cascades National Park, and OLYM is Olympic National Park. *Our classifications are based on the long-term dynamics of wetlands from the VIC runs. As a result, some of our classifications at Mazama Ridge differ from Girdner and Larson's classification from the very dry summer of 1992.

Site Location	Type	Name	Method	Observation Years
Mazama Ridge, MORA, WA	Perennial	Far 2 (Noname) *	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Perennial	High A (LZ16) *	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Perennial	High G (LZ18) *	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Perennial	High D (LZ14)	measurement, iButton	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Permanent	High B (M16) *	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Permanent	High C (LZ15)	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Permanent	Far 1 (LZ19)	measurement	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Permanent	Far 3 (LZ17)	measurement, iButton	2 years (1992, 2012)
Mazama Ridge, MORA, WA	Perennial	M10	measurement	1 year (1992)
Mazama Ridge, MORA, WA	Permanent	LZ12	measurement	1 year (1992)
Palisades, MORA, WA	Permanent	Pal1	measurement	1 year (2012)
Palisades, MORA, WA	Permanent	Pal2	measurement	1 year (2012)
Palisades, MORA, WA	Ephemeral	Pal3	iButton	1 year (2012)
Palisades, MORA, WA	Intermediate	Pal5	measurement	1 year (2012)
Palisades, MORA, WA	Perennial	Pal6	measurement	1 year (2012)
Palisades, MORA, WA	Permanent	Pal8	measurement	1 year (2012)
Palisades, MORA, WA	Intermediate	Pal9	measurement	1 year (2012)
Palisades, MORA, WA	Permanent	Pal10	measurement	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayA	measurement	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayB	measurement	1 year (2012)
Spray Park, MORA, WA	Perennial	SprayC	iButton	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayD	measurement	1 year (2012)

Spray Park, MORA, WA	Ephemeral	SprayE	iButton	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayF	measurement	1 year (2012)
Spray Park, MORA, WA	Ephemeral	SprayG	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayH	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayI	measurement	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayJ1	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayJ2	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayK	measurement	1 year (2012)
Spray Park, MORA, WA	Ephemeral	SprayK.A1	measurement	1 year (2012)
Spray Park, MORA, WA	Ephemeral	SprayK.A2	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayK.A3	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayL	measurement	1 year (2012)
Spray Park, MORA, WA	Intermediate	SprayM	measurement	1 year (2012)
Spray Park, MORA, WA	Ephemeral	SprayN	measurement	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayO	measurement	1 year (2012)
Spray Park, MORA, WA	Permanent	SprayQ	measurement	1 year (2012)
NOCA, WA	Permanent	Pyramid	iButton	1 year (2012)
NOCA, WA	Permanent	Thunder	measurement	1 year (2012)
Deer Lake, OLYM, WA	Perennial	Deer Camp1	measurement	1 year (2012)
Deer Lake, OLYM, WA	Permanent	Deer Camp2	measurement	1 year (2012)
Deer Lake, OLYM, WA	Ephemeral	Deer Camp3	measurement	1 year (2012)
Deer Lake, OLYM, WA	Permanent	Deer Camp4	measurement	1 year (2012)
Deer Lake, OLYM, WA	Perennial	Deer Trail1	measurement	1 year (2012)
Deer Lake, OLYM, WA	Intermediate	Deer Trail2	measurement	1 year (2012)
Deer Lake, OLYM, WA	Permanent	Deer Meadow1.2	measurement	1 year (2012)
Deer Lake, OLYM, WA	Perennial	Deer Meadow3	measurement	1 year (2012)
Deer Lake, OLYM, WA	Ephemeral	Deer Meadow4S	measurement	1 year (2012)

Deer Lake, OLYM, WA	Ephemeral	Deer Meadow5	measurement	1 year (2012)
Deer Lake, OLYM, WA	Permanent	Deer Meadow6	measurement	1 year (2012)
Deer Lake, OLYM, WA	Ephemeral	Deer Meadow7	measurement	1 year (2012)
Deer Lake, OLYM, WA	Ephemeral	Deer Meadow8	measurement	1 year (2012)
Deer Lake, OLYM, WA	Perennial	Deer Meadow9	iButton	1 year (2012)
Deer Lake, OLYM, WA	Intermediate	Deer Meadow10	measurement	1 year (2012)
Deer Lake, OLYM, WA	Permanent	Deer Meadow12	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PM1a	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PM2a	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PM3a	measurement	1 year (2012)
Potholes, OLYM, WA	Permanent	PM3b	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PM4a	measurement	1 year (2012)
Potholes, OLYM, WA	Ephemeral	PM5a	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PM6a	measurement	1 year (2012)
Potholes, OLYM, WA	Ephemeral	PM6c	measurement	1 year (2012)
Potholes, OLYM, WA	Permanent	PotholeA	measurement	1 year (2012)
Potholes, OLYM, WA	Ephemeral	PotholeB	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PotholeC	measurement	1 year (2012)
Potholes, OLYM, WA	Permanent	PotholeD	measurement	1 year (2012)
Potholes, OLYM, WA	Permanent	PotholeE	measurement	1 year (2012)
Potholes, OLYM, WA	Intermediate	PotholeF	measurement	1 year (2012)
Potholes, OLYM, WA	Permanent	PotholeG	measurement	1 year (2012)
Potholes, OLYM, WA	Ephemeral	PotholeH	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL2	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL2a	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL3	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL3a	measurement	1 year (2012)

Upper Lena, OLYM, WA	Permanent	MUL3b	measurement	1 year (2012)
Upper Lena, OLYM, WA	Ephemeral	MUL4	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL7a	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL8	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL9	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL10	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL11	measurement	1 year (2012)
Upper Lena, OLYM, WA	Ephemeral	MUL11a	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL11b	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL11c	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL11d	measurement	1 year (2012)
Upper Lena, OLYM, WA	Intermediate	MUL11e	measurement	1 year (2012)
Upper Lena, OLYM, WA	Permanent	MUL11f	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL11g	measurement	1 year (2012)
Upper Lena, OLYM, WA	Ephemeral	MUL12a	measurement	1 year (2012)
Upper Lena, OLYM, WA	Perennial	MUL12b	measurement	1 year (2012)
Upper Lena, OLYM, WA	Intermediate	MUL13b	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL20	measurement	1 year (2012)
Clear Lake, OLYM, WA	Ephemeral	SL20A (Pond V)	measurement, iButton	2 years (2000, 2012)
Clear Lake, OLYM, WA	Perennial	SL20D	measurement	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL20E	measurement	1 year (2012)
Clear Lake, OLYM, WA	Permanent	SL20F	measurement	1 year (2012)
Clear Lake, OLYM, WA	Permanent	SL20H	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL20I (Pond J)	measurement	2 years (2000, 2012)
Clear Lake, OLYM, WA	Permanent	SL23A (Pond D)	measurement	2 years (2000, 2012)
Clear Lake, OLYM, WA	Perennial	SL23B	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL23C (Pond Y)	measurement	2 years (2000, 2012)

Clear Lake, OLYM, WA	Intermediate	SL23D-M	measurement	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL23D-N	measurement	1 year (2012)
Clear Lake, OLYM, WA	Ephemeral	SL23E	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL23F (Pond K)	measurement	2 years (2000, 2012)
Clear Lake, OLYM, WA	Ephemeral	SL23G	measurement	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL23H (Pond Q)	measurement	1 year (2000, 2012)
Clear Lake, OLYM, WA	Perennial	SL23I	iButton	1 year (2012)
Clear Lake, OLYM, WA	Ephemeral	SL23J	iButton	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL23K	iButton	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL23L (Pond L)	measurement	2 years (2000, 2012)
Clear Lake, OLYM, WA	Perennial	SL26	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL26A	measurement	1 year (2012)
Clear Lake, OLYM, WA	Perennial	SL26B	iButton	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL27B	measurement	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL27D	measurement	1 year (2012)
Clear Lake, OLYM, WA	Intermediate	SL27E.1	measurement	1 year (2012)
Clear Lake, OLYM, WA	Ephemeral	SL27E.2	measurement	1 year (2012)
Clear Lake, OLYM, WA	Ephemeral	SL.3extras	measurement	1 year (2012)
Deschutes NF, OR	Perennial	Muskrat	measurement	2 years (2003, 2006)
Willamette NF, OR	Perennial	Penn	measurement	3 years (2004-2006)
Willamette NF, OR	Intermediate	Unnamed	measurement	3 years (2003, 2005, 2006)
Trinity Alps, CA	Intermediate	Snowmelt	measurement	5 years (2003-2007)

Appendix C. NWI Crosswalk to hydrologic classification

Ephemeral wetlands:
Value = A: Temporarily Flooded - Surface water present for brief periods during the growing season, but the water table usually lies well below the soil surface. Plants that grow both in uplands and wetlands are characteristic of this water regime.
Value = B: Saturated - The substrate is saturated to the surface for extended periods during the growing season, but surface water is seldom present.
Value = J: Intermittently Flooded - The substrate is usually exposed, but surface water is present for variable periods without detectable seasonal periodicity. Weeks, months or even years may intervene between periods of inundation. The dominant plant communities under this regime may change as soil moisture conditions change.

Intermediate wetlands:
Value = C: Seasonally Flooded - Surface water is present for extended periods especially early in the growing season, but is absent by the end of the growing season in most years. The water table after flooding ceases is very variable, extending from saturated to a water table well below the ground surface.
Value = D: Seasonally Well-drained - Surface water is present for extended periods especially early in the growing season. The water table after flooding ceases falls well below the ground surface. (Not used on all maps.)
Value = E: Seasonally Saturated - Surface water is present for extended periods especially early in the growing season, and remains saturated near the surface for most of the growing season. (Not used on all maps.)
Value = F: Semipermanently Flooded - Surface water persists throughout the growing season in most years. When surface water is absent, the water table is usually at or very near the land surface.

Perennial wetlands:
Value = G: Intermittently Exposed - Surface water is present throughout the year except in years of extreme drought.
Value = Z: Intermittently Exposed/Permanent - Exhibits features of both Intermittently Exposed (G) and Permanent (H) water regimes. (Not used on all maps.)

Permanent wetlands:
Value = H: Permanently Flooded - Water covers the land surface throughout the year in all years.

Did not fit our classification:
Value = K: Artificially Flooded - The amount and duration of flooding is controlled by means of pumps or siphons in combination with dikes or dams. Water and waste-water treatment facilities are included in this modifier.
Value = W: Intermittently Flooded/Temporary - Exhibits features of both Intermittently Flooded (J) and Temporary (A) water regimes. (Not used on all maps.)
Value = Y: Saturated/Semipermanent/Seasonals - Exhibits features of the Saturated (B), Semipermanent (F) and Seasonal (C, D and E) water regimes. (Not used on all maps.

Appendix D. Top ranked models for the set of models holding 95% of all model support, by species and life stage.

Rana cascadae **breeding evidence**

AIC	Model	ΔAICc	w_{Ak}
208.8151283	bin~elevation+hydro.class.cons+max.p.emergent+fish	0	0.145101741
209.3735737	bin~elevation+hydro.class.cons+fish+side.habitat	0.558445383	0.109750813
210.9093596	bin~elevation+hydro.class.cons+substrate+fish	2.094231335	0.050923244
210.97057	bin~elevation+PCA+hydro.class.cons+max.p.emergent	2.155441668	0.049388338
211.2010183	bin~elevation+hydro.class.cons+cobble+fish	2.385889978	0.044013225
211.2483608	bin~elevation+PCA+hydro.class.cons+fish	2.433232505	0.042983611
211.3847047	bin~elevation+hydro.class.cons+perc.wooded+fish	2.569576364	0.040150985
211.5637769	bin~elevation+hydro.class.cons+fish+downed.wood	2.748648595	0.036712264
211.6388139	bin~elevation+hydro.class.cons+max.p.emergent+side.habitat	2.823685554	0.035360394
211.9235079	bin~elevation+PCA+hydro.class.cons+side.habitat	3.10837965	0.030668784
212.1192762	bin~hydro.class.cons+max.p.emergent+fish+side.habitat	3.304147897	0.027809042
212.4155635	bin~elevation+hydro.class.cons+max.p.emergent+downed.wood	3.600435154	0.023979938
212.8597856	bin~elevation+PCA+hydro.class.cons+perc.wooded	4.044657299	0.019203768
212.9141314	bin~elevation+hydro.class.cons+max.p.emergent+perc.wooded	4.099003095	0.018688972
212.9168793	bin~elevation+hydro.class.cons+max.p.emergent+cobble	4.101750976	0.018663312
213.0044424	bin~elevation+PCA+hydro.class.cons+downed.wood	4.189314068	0.017863832
213.1282993	bin~elevation+hydro.class.cons+max.p.emergent+substrate	4.313170956	0.016791112
213.1810488	bin~elevation+PCA+hydro.class.cons+cobble	4.365920547	0.016354039
213.4125584	bin~hydro.class.cons+max.p.emergent+substrate+fish	4.597430144	0.014566438
213.7216392	bin~elevation+hydro.class.cons+substrate+downed.wood	4.906510927	0.012480653
213.8023149	bin~elevation+hydro.class.cons+side.habitat+downed.wood	4.987186645	0.011987229
213.8678009	bin~elevation+PCA+hydro.class.cons+substrate	5.05267264	0.011601087
214.0227788	bin~hydro.class.cons+substrate+fish+side.habitat	5.207650456	0.010736079
214.0498798	bin~PCA+hydro.class.cons+max.p.emergent+side.habitat	5.234751458	0.010591581
214.0618838	bin~elevation+hydro.class.cons+substrate+side.habitat	5.246755539	0.0105282
214.197162	bin~elevation+hydro.class.cons+cobble+side.habitat	5.382033738	0.009839632
214.3072093	bin~elevation+hydro.class.cons+cobble+downed.wood	5.492081031	0.009312845
214.398534	bin~PCA+hydro.class.cons+max.p.emergent+fish	5.583405702	0.008897162
214.4447527	bin~elevation+hydro.class.cons+perc.wooded+side.habitat	5.629624403	0.008693912
214.549704	bin~hydro.class.cons+max.p.emergent+perc.wooded+fish	5.734575657	0.008249457
214.8336172	bin~hydro.class.cons+max.p.emergent+fish+downed.wood	6.01848894	0.007157714
214.8490739	bin~hydro.class.cons+max.p.emergent+cobble+fish	6.03394561	0.00710261
214.8509389	bin~hydro.class.cons+max.p.emergent+substrate+side.habitat	6.035810605	0.00709599
214.9840403	bin~elevation+hydro.class.cons+substrate+cobble	6.168911989	0.006639118
215.0355913	bin~elevation+hydro.class.cons+perc.wooded+substrate	6.220462999	0.006470178
215.082078	bin~elevation+hydro.class.cons+perc.wooded+downed.wood	6.266949729	0.006321524
215.1565159	bin~hydro.class.cons+max.p.emergent+substrate+cobble	6.341387607	0.006090568
215.2449219	bin~hydro.class.cons+substrate+fish+downed.wood	6.42979362	0.00582721

215.3441863	bin~hydro.class.cons+max.p.emergent+side.habitat+downed.wood	6.529057989	0.005545053
215.3492442	bin~hydro.class.cons+max.p.emergent+cobble+side.habitat	6.534115857	0.005531048
215.3989091	bin~PCA+hydro.class.cons+max.p.emergent+perc.wooded	6.583780851	0.005395389
215.4008074	bin~hydro.class.cons+max.p.emergent+perc.wooded+side.habitat	6.585679115	0.005390271
215.4157548	bin~elevation+hydro.class.cons+perc.wooded+cobble	6.600626507	0.005350136
215.4174332	bin~hydro.class.cons+max.p.emergent+substrate+downed.wood	6.602304947	0.005345648
215.5235531	bin~PCA+hydro.class.cons+max.p.emergent+substrate	6.708424851	0.005069401
215.7122113	bin~hydro.class.cons+substrate+cobble+fish	6.897082965	0.00461307
215.7349977	bin~PCA+hydro.class.cons+max.p.emergent+cobble	6.919869384	0.004560811
215.7580627	bin~PCA+hydro.class.cons+max.p.emergent+downed.wood	6.942934381	0.004508516
215.7776273	bin~hydro.class.cons+perc.wooded+substrate+fish	6.962498987	0.004464627
216.0052849	bin~PCA+hydro.class.cons+substrate+fish	7.190156558	0.003984281
216.0173227	bin~hydro.class.cons+max.p.emergent+perc.wooded+substrate	7.202194431	0.003960372
216.2637323	bin~hydro.class.cons+substrate+side.habitat+downed.wood	7.448604002	0.003501296
216.5410748	bin~PCA+hydro.class.cons+substrate+side.habitat	7.725946534	0.003047928
216.7133784	bin~hydro.class.cons+substrate+cobble+side.habitat	7.898250151	0.002796336
217.0703645	bin~hydro.class.cons+max.p.emergent+perc.wooded+downed.wood	8.255236212	0.002339219

Ambystoma macrodactylum **breeding evidence**

AIC	Model	ΔAICc	w_{Ak}
181.0526574	bin~hydro.class.cons+perc.wooded+substrate+cobble	0	0.20778837
181.4948944	bin~PCA+hydro.class.cons+substrate+cobble	0.442236938	0.166567668
183.6700824	bin~hydro.class.cons+perc.wooded+substrate+side.habitat	2.617424939	0.056137702
183.9593769	bin~hydro.class.cons+max.p.emergent+perc.wooded+substrate	2.906719438	0.048577497
184.0584347	bin~PCA+hydro.class.cons+perc.wooded+substrate	3.005777261	0.046230118
184.6726671	bin~PCA+hydro.class.cons+cobble+side.habitat	3.620009658	0.034005262
184.7890643	bin~hydro.class.cons+perc.wooded+cobble+side.habitat	3.736406897	0.032082691
184.8003744	bin~hydro.class.cons+substrate+cobble+side.habitat	3.747717003	0.031901774
185.2160496	bin~PCA+hydro.class.cons+max.p.emergent+substrate	4.163392215	0.025915053
185.2741953	bin~hydro.class.cons+max.p.emergent+substrate+cobble	4.221537866	0.025172476
185.5372869	bin~PCA+hydro.class.cons+perc.wooded+cobble	4.484629486	0.022069694
185.8909936	bin~hydro.class.cons+substrate+cobble+downed.wood	4.838336174	0.018492256
185.9215389	bin~hydro.class.cons+substrate+cobble+fish	4.868881435	0.018211976
186.0172572	bin~hydro.class.cons+perc.wooded+substrate+downed.wood	4.964599722	0.017360895
186.0312557	bin~elevation+hydro.class.cons+substrate+cobble	4.978598303	0.017239805
186.1054041	bin~hydro.class.cons+perc.wooded+substrate+fish	5.052746703	0.016612356
186.2684786	bin~elevation+hydro.class.cons+perc.wooded+substrate	5.215821187	0.015311582
186.2685745	bin~PCA+hydro.class.cons+substrate+side.habitat	5.215917111	0.015310847
186.6314633	bin~PCA+hydro.class.cons+perc.wooded+side.habitat	5.578805861	0.012770236
186.7256652	bin~PCA+hydro.class.cons+max.p.emergent+cobble	5.673007766	0.012182692
186.8679021	bin~PCA+hydro.class.cons+substrate+downed.wood	5.815244656	0.011346369

186.9552396	bin~PCA+hydro.class.cons+cobble+fish	5.902582121	0.01086155
187.0762051	bin~PCA+hydro.class.cons+cobble+downed.wood	6.023547658	0.010224086
187.1118297	bin~elevation+PCA+hydro.class.cons+cobble	6.059172257	0.010043584
187.1297258	bin~hydro.class.cons+max.p.emergent+perc.wooded+side.habitat	6.077068359	0.009954114
187.7830091	bin~elevation+hydro.class.cons+perc.wooded+side.habitat	6.730351635	0.007180322
187.8025235	bin~hydro.class.cons+perc.wooded+fish+side.habitat	6.749866054	0.007110603
187.8678066	bin~hydro.class.cons+perc.wooded+side.habitat+downed.wood	6.815149157	0.006882249
187.8937226	bin~PCA+hydro.class.cons+max.p.emergent+perc.wooded	6.841065156	0.006793644
187.9163103	bin~PCA+hydro.class.cons+substrate+fish	6.863652879	0.00671735
187.9283778	bin~hydro.class.cons+max.p.emergent+substrate+downed.wood	6.875720324	0.006676941
187.9378393	bin~elevation+PCA+hydro.class.cons+substrate	6.885181865	0.006645429
188.3311904	bin~hydro.class.cons+max.p.emergent+perc.wooded+cobble	7.278532939	0.005458935
188.3691973	bin~elevation+hydro.class.cons+perc.wooded+cobble	7.316539879	0.005356175
188.4570827	bin~hydro.class.cons+perc.wooded+cobble+fish	7.404425264	0.005125907
188.4639034	bin~hydro.class.cons+perc.wooded+cobble+downed.wood	7.411245988	0.005108456
188.8743508	bin~PCA+hydro.class.cons+max.p.emergent+side.habitat	7.821693357	0.004160659
188.9701992	bin~PCA+hydro.class.cons+perc.wooded+downed.wood	7.917541737	0.003965965
189.006796	bin~elevation+PCA+hydro.class.cons+perc.wooded	7.954138612	0.003894054
189.0252676	bin~PCA+hydro.class.cons+perc.wooded+fish	7.972610213	0.003858255
189.0469631	bin~hydro.class.cons+max.p.emergent+substrate+side.habitat	7.994305688	0.003816628
189.0650637	bin~hydro.class.cons+cobble+fish+side.habitat	8.012406262	0.003782242
189.3722236	bin~hydro.class.cons+max.p.emergent+cobble+side.habitat	8.31956622	0.003243772
189.3731081	bin~hydro.class.cons+cobble+side.habitat+downed.wood	8.320450633	0.003242338
189.6030413	bin~PCA+hydro.class.cons+max.p.emergent+downed.wood	8.550383918	0.002890207
189.6079489	bin~elevation+hydro.class.cons+cobble+side.habitat	8.555291452	0.002883124
189.6408435	bin~hydro.class.cons+max.p.emergent+substrate+fish	8.588186112	0.002836092

Ambystoma macrodactylum **adult presence**

AIC	Model	ΔAICc	w_{Ak}
146.3656039	bin~PCA+perc.wooded+fish+side.habitat	0	0.372647056
149.5125158	bin~hydro.class.cons+perc.wooded+fish+side.habitat	3.146911882	0.077259957
150.298154	bin~PCA+perc.wooded+substrate+fish	3.932550065	0.052162128
150.9105203	bin~PCA+substrate+fish+side.habitat	4.544916373	0.038404458
151.3790392	bin~PCA+perc.wooded+substrate+side.habitat	5.013435268	0.030383938
151.4453756	bin~PCA+perc.wooded+fish+downed.wood	5.079771694	0.029392687
151.4769375	bin~PCA+perc.wooded+cobble+fish	5.111333553	0.028932484
151.6515424	bin~elevation+PCA+perc.wooded+fish	5.285938413	0.026513725
151.6706177	bin~PCA+max.p.emergent+perc.wooded+fish	5.30501376	0.026262048
151.7769579	bin~PCA+perc.wooded+side.habitat+downed.wood	5.411353998	0.024902165
152.2763509	bin~PCA+perc.wooded+cobble+side.habitat	5.910746959	0.019399713
152.3004594	bin~PCA+hydro.class.cons+perc.wooded+side.habitat	5.934855424	0.019167268

152.3181757	bin~PCA+max.p.emergent+perc.wooded+side.habitat	5.952571762	0.018998231
152.3425257	bin~elevation+PCA+perc.wooded+side.habitat	5.976921732	0.01876833
152.3808708	bin~hydro.class.cons+perc.wooded+cobble+side.habitat	6.01526682	0.018411921
152.5087482	bin~hydro.class.cons+perc.wooded+side.habitat+downed.wood	6.143144208	0.017271533
152.5631736	bin~hydro.class.cons+max.p.emergent+perc.wooded+side.habitat	6.197569625	0.016807865
152.6045253	bin~elevation+hydro.class.cons+perc.wooded+side.habitat	6.238921383	0.016463916
152.8426206	bin~perc.wooded+fish+side.habitat+downed.wood	6.477016674	0.014616096
152.8848066	bin~max.p.emergent+perc.wooded+fish+side.habitat	6.519202612	0.014311028
153.143931	bin~hydro.class.cons+perc.wooded+substrate+side.habitat	6.778327087	0.012571951
153.5347309	bin~perc.wooded+cobble+fish+side.habitat	7.169126905	0.010340501
153.5541787	bin~elevation+perc.wooded+fish+side.habitat	7.188574757	0.010240438
154.016314	bin~PCA+hydro.class.cons+perc.wooded+fish	7.650710021	0.00812769
154.3457646	bin~max.p.emergent+perc.wooded+side.habitat+downed.wood	7.980160671	0.00689331
154.4313299	bin~elevation+perc.wooded+side.habitat+downed.wood	8.06572599	0.006604616
154.4854623	bin~perc.wooded+cobble+side.habitat+downed.wood	8.119858315	0.006428252
154.9011587	bin~perc.wooded+substrate+fish+side.habitat	8.535554787	0.005221864
154.9203811	bin~PCA+fish+side.habitat+downed.wood	8.554777109	0.005171916
154.9278548	bin~elevation+max.p.emergent+perc.wooded+side.habitat	8.562250805	0.005152625
154.9935442	bin~max.p.emergent+perc.wooded+cobble+side.habitat	8.627940205	0.004986138
155.1511214	bin~PCA+substrate+fish+downed.wood	8.785517489	0.004608364
155.2723203	bin~elevation+PCA+substrate+fish	8.906716402	0.004337393
155.2748914	bin~elevation+perc.wooded+cobble+side.habitat	8.909287486	0.004331821
155.6144062	bin~PCA+substrate+cobble+fish	9.248802299	0.003655492
155.6605172	bin~PCA+max.p.emergent+substrate+fish	9.294913301	0.003572177
155.9904684	bin~perc.wooded+substrate+side.habitat+downed.wood	9.624864429	0.0030289
155.9914367	bin~PCA+substrate+side.habitat+downed.wood	9.625832773	0.003027434
156.038475	bin~max.p.emergent+perc.wooded+substrate+side.habitat	9.672871023	0.002957062
156.3076981	bin~PCA+cobble+fish+side.habitat	9.94209413	0.002584636
156.3150119	bin~PCA+hydro.class.cons+substrate+side.habitat	9.949407945	0.002575201
156.3697502	bin~elevation+perc.wooded+substrate+side.habitat	10.00414627	0.002505676

Ambystoma gracile **breeding evidence**

AIC	Model	ΔAICc	w_{Ak}
141.1089676	bin~elevation+hydro.class.cons+perc.wooded+fish	0	0.634827453
145.5333868	bin~hydro.class.cons+max.p.emergent+perc.wooded+fish	4.42441922	0.069487274
146.4004835	bin~PCA+hydro.class.cons+perc.wooded+fish	5.291515965	0.045041994
146.5578857	bin~hydro.class.cons+perc.wooded+fish+downed.wood	5.448918078	0.041633045
146.6461614	bin~hydro.class.cons+perc.wooded+cobble+fish	5.537193802	0.039835415
146.6537242	bin~hydro.class.cons+perc.wooded+fish+side.habitat	5.544756582	0.039685066
147.7265681	bin~elevation+max.p.emergent+perc.wooded+fish	6.617600569	0.023209297
148.3076882	bin~elevation+PCA+perc.wooded+fish	7.198720616	0.017356949

148.9040987	bin~elevation+hydro.class.cons+max.p.emergent+perc.wooded	7.795131079	0.012881442
149.2214143	bin~elevation+PCA+hydro.class.cons+fish	8.112446763	0.010991584
149.527857	bin~hydro.class.cons+perc.wooded+substrate+fish	8.418889377	0.009430117
150.0664703	bin~elevation+hydro.class.cons+perc.wooded+side.habitat	8.957502738	0.007203751
150.1003568	bin~elevation+hydro.class.cons+fish+downed.wood	8.991389253	0.007082724
150.3948294	bin~elevation+hydro.class.cons+max.p.emergent+fish	9.285861856	0.006113028
151.1030004	bin~elevation+PCA+hydro.class.cons+perc.wooded	9.994032774	0.004290215
151.1088979	bin~elevation+hydro.class.cons+perc.wooded+downed.wood	9.999930293	0.004277583
151.1180009	bin~elevation+hydro.class.cons+perc.wooded+cobble	10.00903331	0.004258158
151.3342013	bin~PCA+max.p.emergent+perc.wooded+fish	10.22523375	0.003821857
151.5117765	bin~hydro.class.cons+max.p.emergent+perc.wooded+side.habitat	10.40280895	0.003497151
151.5838042	bin~elevation+hydro.class.cons+cobble+fish	10.47483663	0.003373446
151.7775115	bin~hydro.class.cons+max.p.emergent+perc.wooded+downed.wood	10.66854389	0.00306204
151.7883141	bin~PCA+hydro.class.cons+max.p.emergent+perc.wooded	10.67934653	0.003045545
151.9094687	bin~elevation+hydro.class.cons+fish+side.habitat	10.80050108	0.002866531
152.0082919	bin~hydro.class.cons+max.p.emergent+perc.wooded+cobble	10.89932434	0.002728334